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Forecasting ICU Census by Combining Time Series and Survival Models

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OBJECTIVES: Capacity planning of ICUs is essential for effective management of health safety, quality of patient care, and the allocation of ICU resources. Whereas ICU length of stay (LOS) may be estimated using patient information such as severity of illness scoring systems, ICU census is impacted by both patient LOS and arrival patterns. We set out to develop and evaluate an ICU census forecasting algorithm using the Multiple Organ Dysfunction Score (MODS) and the Nine Equivalents of Nursing Manpower Use Score (NEMS) for capacity planning purposes.

DESIGN: Retrospective observational study.

SETTING: We developed the algorithm using data from the Medical-Surgical ICU (MSICU) at University Hospital, London, Canada and validated using data from the Critical Care Trauma Centre (CCTC) at Victoria Hospital, London, Canada.

PATIENTS: Adult patient admissions (7,434) to the MSICU and (9,075) to the CCTC from 2015 to 2021.

INTERVENTIONS: None.

MEASUREMENTS AND MAIN RESULTS: We developed an Autoregressive integrated moving average time series model that forecasts patients arriving in the ICU and a survival model using MODS, NEMS, and other factors to estimate patient LOS. The models were combined to create an algorithm that forecasts ICU census for planning horizons ranging from 1 to 7 days. We evaluated the algorithm quality using several fit metrics. The root mean squared error ranged from 2.055 to 2.890 beds/d and the mean absolute percentage error from 9.4% to 13.2%. We show that this forecasting algorithm provides a better fit when compared with a moving average or a time series model that directly forecasts ICU census. Additionally, we evaluated the performance of the algorithm using data during the global COVID-19 pandemic and found that the error of the forecasts increased proportionally with the number of COVID-19 patients in the ICU.

CONCLUSIONS: It is possible to develop accurate tools to forecast ICU census. This type of algorithm may be important to clinicians and managers when planning ICU capacity as well as staffing and surgical demand planning over a short time horizon.

KEY WORDS: ARIMA, healthcare management, intensive care, survival analysis, time series, forecasting

Intensive care scoring systems are widely used to predict patient outcome, characterize severity of patient illness, and manage resources (1). Forecasting ICU census based on illness severity scoring systems may help improve the quality of care administered in the facility and support capacity management. In Ontario Canada, the Multiple Organ Dysfunction Score (MODS) (2, 3) (**Supplementary Table 1**, http://links.lww.com/CCX/B190) and the Nine Equivalents of Nursing Manpower Use Score (NEMS) (4–6) (**Supplementary Table 2**, http://links.lww.com/CCX/B190) are recorded on ICU patient admission for reporting purposes.

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KEY POINTS

Question: How can we forecast ICU census over a short time horizon?

Findings: Time series and survival analysis can be combined to accurately forecast ICU census.

Meanings: This type of algorithm may be important to clinicians and managers when planning ICU capacity as well as staffing and surgical demand.

Many tools using scoring systems have been proposed to help ICU practitioners predict patient length of stay (LOS) or for benchmarking purposes (7–9). These rely predominantly on the Acute Physiology and Chronic Health Evaluation score, the Simplified Acute Physiology Score, and the Sequential Organ Function Assessment score (10–12). Some regression models only account for 5–20% of the individual variation in ICU LOS (13, 14) while still being statistically significant in predicting long-stay patients (13) and readmission (15). This fact is one of the reasons why researchers seem reticent to use their models for individual patient's LOS predictions (7, 12, 16–18) but are more confident to recommend them for ICU benchmarking (19).

Time series models related to ICU health care have been developed primarily for predicting clinical outcomes (20, 21) and mortality (22). Recently, time series methodologies have been developed to aid ICU management during the COVID-19 pandemic (23–25).

Survival analysis models applied to ICUs tend to focus on hazard ratios (26–28). Clark and Ryan (26) found that age, Glasgow Coma Score, and abbreviated injury scores were significant predictors of the rates of ICU deaths and discharge with effects that were variable in different time intervals. Moran et al (28). compared Cox and Accelerated Failure Time (AFT) survival models and advocate for the inclusion of time-varying covariates in ICU survival analysis as they show hazard ratios vary over time. Recently, Vekaria et al (29). introduced an AFT survival model to predict LOS of ICU patients with COVID-19 in the United Kingdom. Their model; however, did not include patients without COVID-19 or new patients arriving in the ICU. To forecast ICU census, all present and future patients need to be considered.

We developed an ICU census forecasting algorithm that combines time series models to forecast future arrivals with survival models using MODS and NEMS to predict ICU LOS to forecast ICU census over a short-term planning horizon. We evaluate the performance of the algorithm before the COVID-19 pandemic, and we also evaluate the performance of the algorithm during the pandemic.

MATERIALS AND METHODS

Data

Data were collected from the London Health Science Centre, a publicly funded, tertiary care teaching hospital with two campuses, University Hospital, which includes a Medical–Surgical ICU (MSICU), and Victoria Hospital, which includes a Critical Care Trauma Centre (CCTC), located in London, ON, Canada (**Supplementary Table 3**, http://links.lww.com/CCX/B190). The MSICU is a 25-bed adult ICU caring for neurosurgery, transplant, medical, and general surgery patients. The CCTC is a 30-bed adult ICU caring for trauma patients. We developed the model using data from the MSICU, and used data from the CCTC to validate our approach. The study was conducted in accordance with ethical standards of the Western University Ethics Review Board, and the need for informed consent was waived (Study Title: Intensive Care bed planning in the London Health Sciences Center: Analytical models for step-down capacity planning, October 2014, #1005583) and Helsinki Declaration of 1975.

Our study includes all patient admissions to the MSICU from January 1, 2015, to December 31, 2021. The first three years were used to develop the model, and the last four years (2 years before the pandemic and 2 years during the pandemic) were used to evaluate model performance. As is common in the literature (12, 30), we excluded records with a LOS of less than 4 hours or more than 60 days, as well as records with LOS recorded as 0 days or more than 120 years old.

We considered only the variables available on the day of admission including age, sex, admission source, diagnosis group (see **Supplementary Section 1**, http://links.lww.com/CCX/B190), category (medical or surgical), scheduled surgery, ventilation, MODS, and NEMS. We defined four additional binary variables using information available on the day of admission using each patient's admission dates and admission source:

- Readmission A (1 if the patient returned to the ICU from a step-down unit or ward),
- Readmission B (1 if the patient was discharged from the hospital and returned to the ICU in < 7 d),
- Congested (1 if ICU census > 80%), and
- Censored (1 if the patient outcome was known).

Patients were categorized as either outcome known if deceased, transferred to another ward, or returned home; or outcome unknown if transferred to another hospital or still in the ICU at the end of the period. The censored patients were included in the analysis to account for their contribution up to the time of their transfer.

Forecasting Arrivals and LOS Prediction

We developed an autoregressive integrated moving average (ARIMA) model to forecast the number of patients that arrive daily at the ICU. We investigated model fit for the first 3 years together (2015–2017), and as a robustness check, for each of the 3 years individually.

We developed two survival models to predict LOS. The first uses information that would be known at the time that a census forecast is being made and would apply to all patients in the ICU on that day. We considered several functional forms for the survival models, including exponential, log-normal, Weibull, and log-logistic using the variable selection methods for parametric survival models provided by Zhang (31). We assessed model fit using residual analysis, Akaike information criterion (AIC) scores, and concordance.

The second survival model did not use any patient-specific information. This model was used to forecast LOS for patients who arrive in the future, and whose characteristics are not known at the time of forecasting the ICU census. Since the characteristics of the future patients who arrive in the ICU are unknown, we used an intercept-only survival model to predict their LOS probabilities.

Algorithm for Forecasting Census

Our algorithm combined the full and intercept-only survival models and time series model to obtain forecasts for ICU census over a short-term planning horizon (see **Supplementary Section 2**, http://links.lww.com/CCX/B190). We generated the conditional LOS probabilities from the full survival model for each patient present in the ICU on the day of the forecast. The model parameters are dependent on patient characteristics including MODS and NEMS, and therefore, each patient has a unique LOS probability function. The conditional LOS probabilities were aggregated for each patient cohort on each day to forecast the future daily ICU census among those present.

We generated the LOS probabilities from the intercept-only survival model to forecast the arrivals' LOS probabilities. We multiplied the daily forecasted arrivals produced by the time series model and the LOS probabilities from the intercept-only model to forecast the number of arrivals remaining in the ICU. For example, if the number of patients forecasted to arrive 1 day ahead was 3 and the LOS probability to remain in the facility 2 days ahead was 0.85, then the expected number of those arrivals still occupying an ICU bed in 2 days is $3 \times 0.85 = 2.55$.

The expected ICU census on any future day is obtained by adding the expected number of patients remaining in the ICU among those present (the aggregated LOS probabilities generated by the full survival model), and the expected number of new arrivals remaining in the ICU (the number of daily forecasted arrivals from the time series model multiplied by the LOS probabilities generated by the intercept-only survival model).

Algorithm Performance

We used root mean squared error (RMSE) and mean absolute percentage error (MAPE) to evaluate the quality of our forecasting algorithm. We also counted the number of times that the forecasted census was within ± 1, 2, and 5 beds of the true census for each day of the planning horizon. We also evaluated the performance of the algorithm by using an independent data series from the CCTC.

We compared the performance of our forecasting algorithm with two alternate models. The first was a 7-day moving average of ICU census, and the second was an ARIMA(p, d, q) model fitted directly to ICU census data, where p is the number of lag observations, d is the number of times the observations were differenced (e.g., the first differencing value is the difference between the current time and the previous time), and q is the size of the moving average window. We selected the best ARIMA model based on the AIC scores.

The moving average forecaster produces forecasts as follows (32): the 1-day-ahead forecast is equal to the average of the previous 7 observed days. The 2-day-ahead forecast is equal to the average of the previous 6 observed days and the 1-day-ahead forecast. In general, the n-day-ahead forecast is the average of the $8 - n$ previous observed days and the $n - 1$-day-ahead forecasts. Forecasts for the ARIMA were made in the standard way described by Hyndman and Athanasopoulos (33).

RESULTS

There were a total of $n = 7{,}714$ patients admitted into the MSICU with a LOS ranging from 0 to 232 days. After exclusions, there were $n = 7{,}434$ patients for our analysis. There were $n = 3{,}174$ patients in the training set (2015–2017) and $n = 4{,}540$ in the validation set (2018–2021). Patient characteristics are shown in **Supplementary Table 4** (http://links.lww.com/CCX/B190). The data were strongly right-skewed with 65% of the patients having a LOS of less than 4 days, and 2% of the patients having a LOS of more than 30 days.

Forecasting Arrivals

The average daily arrivals for the training and validation sets were 2.80 and 2.67. The unit root tests indicated that the time series is stationary. This modified the ARIMA to an ARMA model since the order of differencing, d, is set to zero. **Supplementary Table 5** (http://links.lww.com/CCX/B190) shows the RMSE for the ARMA models using cross-validation for time series (33) with a moving 60-day window from January 1, 2015, to December 31, 2017. An ARMA(1, 0) (i.e., AR(1)) model was used for forecasting arrivals fitted with the previous 60 days. **Supplementary Figure 1** (http://links.lww.com/CCX/B190) shows the 1-day-ahead forecasts using AR(1) and MA(1) for each day in 2018. The AR(1) and MA(1) models outperform a fixed average approach based on the RMSE. For example, the mean RMSE forecasts for the AR(1) and fixed average approach are 1.54 and 1.65 arrivals/d. The AR(1) has the advantage of adjusting for sudden increases and decreases of new patients arriving to the ICU.

Survival Models

The log-normal LOS model provided the best fit among all the survival models analyzed based on the residual analysis (**Supplementary Figs. 2** and **3**, http://links.lww.com/CCX/B190) and the AIC scores (**Supplementary Table 6**, http://links.lww.com/CCX/B190). The AIC scores for the LOS models use the scoring systems in addition to the other selected covariates.

The variable selection methods indicated the following variables are significantly associated with LOS in addition to MODS and NEMS: age, admission source, diagnosis group, scheduled surgery, ventilation, and readmission A. The variables that were not significantly associated with LOS were sex, patient category (medical or surgical), readmission B, and ICU congestion. The selected covariates ordered by importance are shown in **Supplementary Figure 4** (http://links.lww.com/CCX/B190).

The predictor variables, estimates of the coefficients, standard errors, z values, and p values for the log-normal LOS model are shown in **Table 1**. The likelihood ratio test indicated that the model, on the whole, is significantly better than one which does not include any covariates ($p < 0.001$). The concordance index for the model was 0.63.

Forecasting ICU Census at MSICU

The ICU census forecasts were estimated for each day from January 1, 2018, to December 31, 2021. The RMSE and MAPE ranged from 2.165 to 3.270 beds/d and 9.4% to 13.9%, respectively. From January 1, 2018, to February 29, 2020, the RMSE and MAPE ranged from 2.055 to 2.890 beds/d and 9.4% to 13.2%. Performance was slightly worse during the pandemic: from March 1, 2020, to December 31, 2021, the RMSE and MAPE ranged from 2.288 to 3.202 beds/d and 9.4% to 14.6%.

Figure 1 shows the ICU census forecasts for 1, 3, 5, and 7-day planning horizons for each day of 2018. The curves show that as the planning horizon increases, the forecasts approach the observed average census. **Supplementary Figure 5** (http://links.lww.com/CCX/B190) shows the distributions of the forecast errors (observed census minus forecasted census) for planning horizons of 1–7 days.

Table 2 shows the percentage of observed ICU census within ± 1, 2, and 5 beds of the ICU census forecasts for planning horizons of 1, 3, 5, and 7 days.

We compared our census forecasting algorithm to a 7-day moving average forecaster and a time series model that forecasts ICU census. Based on the AIC scores and unit root tests the ARMA(2, 1) provided the

TABLE 1.
The Log-Normal Length of Stay Model

Log-Normal LOS Model (n=3,174)	Coefficient	SE	z	p
Intercept	−0.382	0.122	−3.11	< 0.01
MODS	0.041	0.007	5.40	< 0.01
NEMS	0.022	0.003	6.99	< 0.01
Age				
18–39 (reference)	–	–	–	–
40–79	0.097	0.068	1.42	0.155
80 and above	−0.150	0.082	−1.83	0.066
Admission source				
Emergency department (reference)	–	–	–	–
Operating room	−0.203	0.074	−2.73	< 0.01
Other external	0.222	0.058	3.78	< 0.01
Step-down unit	0.250	0.083	2.98	< 0.01
Unit ward	0.065	0.063	1.03	0.301
Diagnosis Group				
Cardiovascular (reference)	–	–	–	–
Gastrointestinal	0.125	0.080	1.57	0.117
Neurological	0.065	0.068	0.95	0.341
Other	0.094	0.067	1.40	0.160
Respiratory	0.286	0.067	4.25	< 0.01
Readmission A				
No (reference)	–	–	–	–
Yes	0.287	0.093	3.09	< 0.01
Scheduled surgery				
No (reference)	–	–	–	–
Yes	−0.186	0.094	−1.98	0.042
Ventilation				
No (reference)	–	–	–	–
Yes	0.298	0.065	4.55	< 0.01

LOS = length of stay; MODS = Multiple Organ Dysfunction Score, NEMS = Nine Equivalents of Nursing Manpower Use Score. Intercept, predictor variables, maximum likelihood coefficients (β), SES, *z* values, and *p* values for the Medical-Surgical ICU.

best fit for ICU census. Our ICU census algorithm outperformed the 7-day moving average forecaster and the ARMA(2, 1) based on the performance measures shown in **Table 3**. For example, the RMSE for the moving average for 3-, 5-, and 7-day ahead forecasts from January 1, 2018, to December 31 2021 were 2.959, 3.191, and 3.326 beds/day compared to our algorithm of 2.857, 3.132, and 3.270 beds/day.

We compared the three different forecasting methods using the Nemenyi/multiple comparisons with the best test (34, 35) which indicated our algorithm forecasts are significantly different ($p < 0.01$). We used the Diebold-Mariano test for predictive accuracy (36) and found that our algorithm forecasts are more accurate than the moving average and the ARMA(2, 1) models ($p < 0.01$). These tests are used to determine which forecaster is best when the performance measures (RMSE, MAPE, etc.) are similar.

Supplementary Figures 6-9 (http://links.lww.com/CCX/B190) show the pointwise prediction intervals for the ICU census forecasts for planning horizons 1 to 7 days. As the planning horizon increases, our

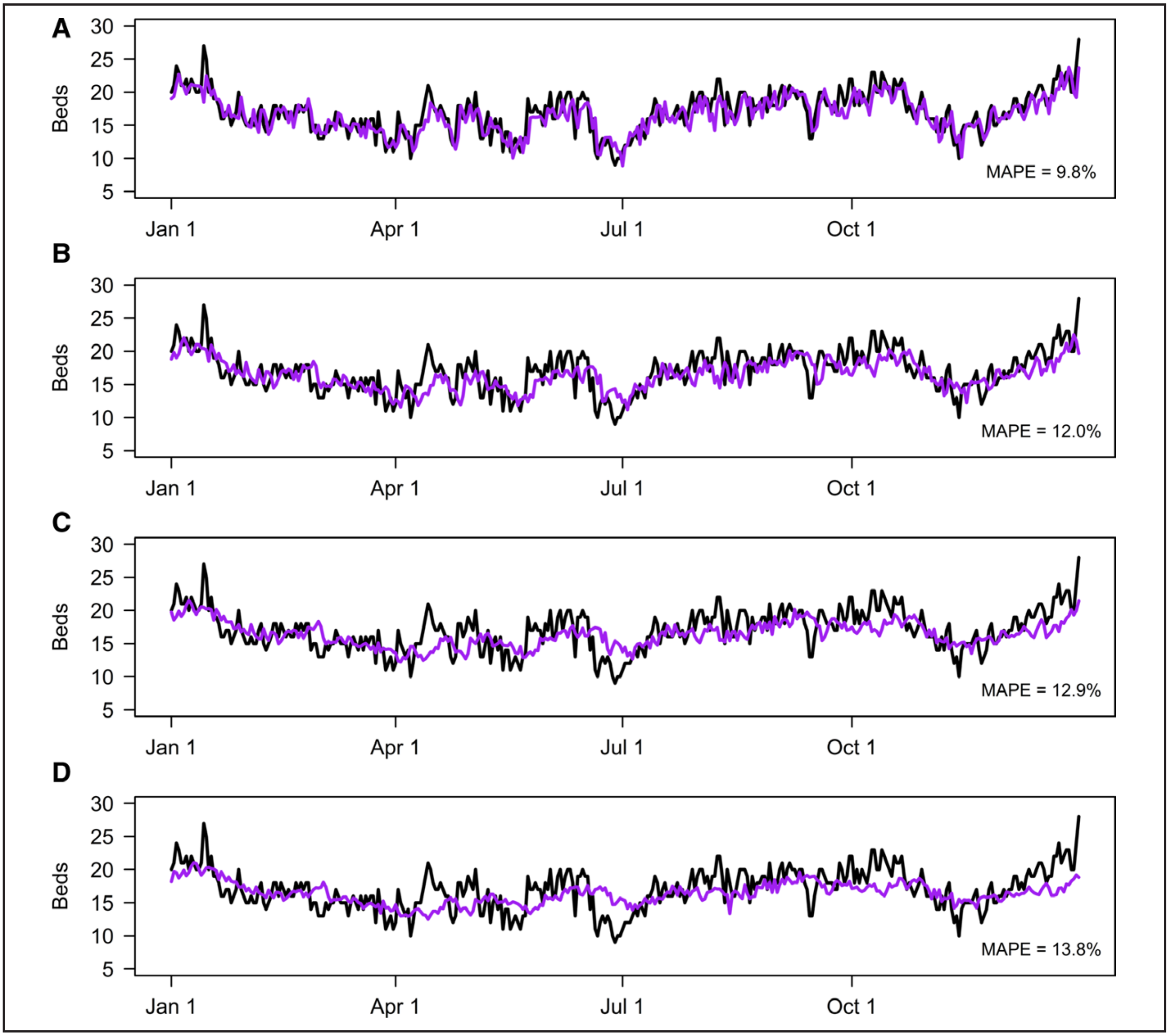

Figure 1. The observed ICU census (black) and forecasted ICU census (*purple*) for 1-day (**A**), 3-day (**B**), 5-day (**C**), and 7-day (**D**) planning horizons for the Medical-Surgical ICU in 2018. MAPE = mean absolute percentage error.

forecasting method converges to the observed average daily census. However, the moving average and ARMA (2, 1) forecasts do not have this behavior and do not converge to the observed average daily census.

Validation Using CCTC Data

We tested the performance of our algorithm using data from the CCTC at Victoria Hospital as external validation. We obtained similar results compared to the MSICU. From January 1, 2018, to December 31, 2021, the RMSE and MAPE ranged from 2.350 to 3.316 beds/d and 3.8% to 12.8%. From January 1, 2018, to February 29, 2020, the RMSE and MAPE ranged from 2.216 to 3.0 beds/d and 8.1% to 11.0%, and during the pandemic, March 1, 2020, to December 31, 2021, the RMSE and MAPE ranged from 2.403 to 3.437 beds/d and 9.1% to 13.5%.

Figure 2 shows the monthly RMSE of the 1-day ahead census forecasts for the MSICU and CCTC from January 1, 2018, to December 31, 2021. We found that the error of the forecasts increased proportionally to the number of COVID-19 patients in the ICU. The monthly RMSE for the 1, 3, 5, and 7-day ahead forecasts for both facilities are shown in **Supplementary Figure 10** (http://links.lww.com/CCX/B190). As the

TABLE 2.
Percentage of Observed ICU Census Within ± 1, 2, and 5 Beds of the ICU Census Forecasts for Planning Horizons 1, 3, 5, and 7 Days for the Medical-Surgical ICU

Percentage of Observed ICU Census	1 d	3 d	5 d	7 d	Mean
Overall: January 1, 2018, to December 31, 2021					
± 1 bed	36.0	29.2	27.2	26.1	28.9
± 2 beds	64.9	53.6	49.2	47.8	52.9
± 5 beds	98.2	91.8	90.1	87.5	91.4
Prepandemic: January 1, 2018, to February 29, 2020					
± 1 bed	38.0	31.9	27.0	26.6	30.6
± 2 beds	66.1	58.0	52.8	52.2	56.5
± 5 beds	98.7	94.2	93.3	91.1	94.1
Pandemic: March 1, 2020, to December 31, 2021					
± 1 bed	33.6	26.1	27.5	25.5	26.9
± 2 beds	63.6	48.4	45.1	42.7	48.7
± 5 beds	97.5	89.0	86.3	83.1	88.3

The mean percentage is for days 1–7.

TABLE 3.
Comparison of Forecasting ICU Census Models using Root Mean Square Error and Mean Absolute Percentage Error for the Medical-Surgical ICU

	RMSE (MAPE)				
Forecasting Method	1 d	3 d	5 d	7 d	Mean
Our algorithm					
Overall: January 1, 2018, to December 31, 2021	2.165 (9.4)	2.857 (12.2)	3.132 (13.3)	3.270 (13.9)	2.899 (12.4)
Prepandemic: January 1, 2018, to February 29, 2020	2.055 (9.4)	2.580 (11.6)	2.774 (12.7)	2.890 (13.2)	2.613 (11.9)
Pandemic: March 1, 2020, to December 31, 2021	2.288 (9.4)	3.153 (13.0)	3.507 (14.1)	3.667 (14.6)	3.202 (13.0)
Moving average					
Overall: January 1, 2018, to December 31, 2021	2.544 (11.4)	2.959 (13.3)	3.191 (14.3)	3.326 (14.8)	3.022 (13.5)
Prepandemic: January 1, 2018, to February 29, 2020	2.255 (10.7)	2.586 (12.2)	2.760 (13.1)	2.844 (13.5)	2.626 (12.5)
Pandemic: March 1, 2020, to December 31, 2021	2.848 (12.3)	3.346 (14.5)	3.634 (15.7)	3.818 (16.4)	3.431 (14.8)
ARMA (2, 1)					
Overall: January 1, 2018, to December 31, 2021	2.047 (9.1)	2.931 (13.1)	3.283 (14.7)	3.458 (15.4)	2.977 (13.3)
Prepandemic: January 1, 2018, to February 29, 2020	1.911 (9.0)	2.561 (12.2)	2.803 (13.4)	2.920 (14.1)	2.584 (12.3)
Pandemic: March 1, 2020, to December 31, 2021	2.196 (9.2)	3.315 (14.2)	3.772 (16.2)	4.001 (17.0)	3.382 (14.4)

RMSE = root mean square error, MAPE = mean absolute percentage error.
The mean RSME and MAPE are for days 1–7.

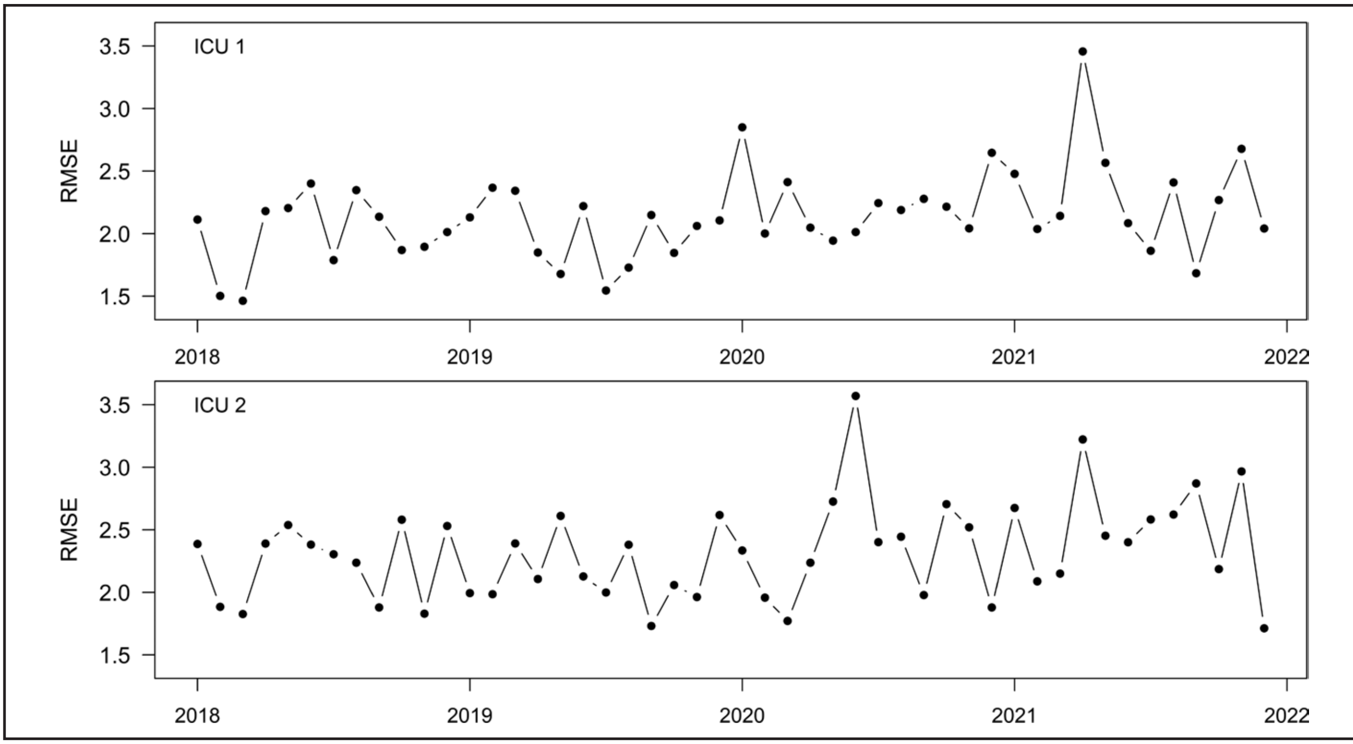

Figure 2. The monthly root mean square error (RMSE) for the 1-day ahead census forecasts for the Medical-Surgical ICU and Critical Care Trauma Centre facilities from January 1, 2018, to December 31, 2021.

planning horizon increases the error of the forecasts also increases.

DISCUSSION

We have presented an ICU capacity planning algorithm that combines time series and survival models to forecast ICU census over a short time horizon. We showed that our algorithm outperforms simple ICU forecasting methods based on performance measures. Our algorithm uses patient characteristics, including MODS and NEMS intensive care scoring systems. The combination of arrivals forecasting with survival models to predict patient LOS results in a better fit when compared to models based on only ICU census data (Table 3). Previous work has shown a link between high ICU census and adverse outcomes (37–39), highlighting the need for tools that help to predict ICU census.

MODS and NEMS were recently analyzed as part of an ICU mortality study using a multivariate logistic regression model (40, 41). These scores were found to be significantly associated with ICU mortality. We are not aware of studies that used MODS and NEMS for ICU LOS prediction of individual patients or to forecast ICU census.

Previous studies have shown that ICU LOS models of individual patients suffer from unreliable LOS predictions at the patient level, being more useful for benchmarking purposes. One explanation is that many factors influence LOS, and parametric LOS models are only able to include a subset of those factors. Indeed, the goodness of fit measures on some previous regression models suggests that only 5-20% of the variation in LOS is explained by the models (13, 14). A second explanation is that the empirical LOS distribution for ICU patients is very highly skewed, with most patients leaving within a few days, and a small number staying for a very long time. This was true in our sample where 65% of patients had LOS < 4 days, and 2% had LOS > 30 days. We used a log-normal survival model to account for the skewed nature of ICU LOS, and we showed that aggregating the LOS probabilities of existing and future patients can result in accurate forecasts of census. The literature contains a limited number of mathematical models to predict future patient census in ICUs. Capan et al (42). proposed and compared ARIMA and linear regression models to predict future neonatal ICU (NICU) census. They found that time series models performed better than a fixed average census approach. Koestler et al (43). proposed an ensemble-based methodology for forecasting hospital census. Using the current census count and the number of daily arrivals and departures from a neonatal ICU (NICU), they showed how a seasonality-adjusted Poisson autoregressive (PAR) model substantially improves census forecasts. An ARIMA was applied to ICU data to predict long-term demand in Australia and New Zealand (44). A real-time LOS model based on a network of infinite server queues driven by a Poisson Arrival Location Model (PALM) was developed to support ICU and ward capacity management during the first peak of COVID-19 in the Netherlands (45). Nguyen et al developed a time series model to forecast COVID-19 hospital census in a collection of hospitals in North Carolina (46).

Our proposed forecasting algorithm differs from other studies that forecast ICU census. Unlike the linear regression models with time series predictors proposed by Capan et al (42)., survival models have the advantage of providing unique ICU LOS probability functions for each patient that can be pooled to forecast ICU census among those present. In addition, Capan et al (42). and Koestler et al (43) forecasting methods were based on data from NICU facilities which may differ significantly from adult ICU. Baas et al (45) proposed a simulation method specifically designed to forecast ICU census with a focus on the maximum census during the COVID-19 pandemic whereas our model was developed for the purpose of forecasting daily ICU census in a nonepidemic environment absent of extreme increases in ICU admissions. Corke et al (44) proposed a model designed to predict long-term ICU demand. In contrast, our forecasting algorithm focuses on short-term planning by combining time series and survival models to forecast ICU census over a 7-day planning horizon. We are not aware of any algorithms designed to forecast adult ICU census by combining time series and survival models, nor are we aware of any census forecasting tools that make use of NEMS and MODS.

Other papers have attempted to forecast patient census (9, 42–46). We are not able to directly compare algorithms (e.g., by using another algorithm with our data set) because either the setting is different (e.g., NICU vs ICU) or the independent variables are different. However, we can compare the reported performance measures shown in **Table 4**. The RMSE and MAPE values produced by our algorithm compare favorably to those produced by other census forecasting methods.

Our study has limitations. The LOS predictions of individual patients with long stays are underestimated, which could affect model performance when

TABLE 4.
Comparison of Forecasting ICU Census Models with Root Mean Square Error and Mean Absolute Percentage Error

Authors	RMSE (MAPE)				
	1 d	3 d	5 d	7 d	Mean (1–7 d)
Our algorithm	2.055 (9.4)	2.580 (11.6)	2.774 (12.7)	2.890 (13.2)	2.613 (11.9)
Koestler–w/patient information	(2.00)	(3.44)	(4.35)	(5.12)	–
Koestler–without patient info	(2.30)	(4.93)	(7.14)	(7.18)	–
Tello–with weekend	4.36 (3.81) for 1-d ahead, 5.77 (4.89) for 2-d ahead				
Tello–without weekend	7.41 (6.15) for 1-d ahead, 14.1 (11.59) for 2-d ahead				
Nguyen–multivariate time series	(5.9)–(13.4) for 1-d ahead				
	January 14–20, 2013	April 1–7, 2013	May 3–9, 2013	Mean of all predictions	
Capan–fixed mean	12.294 (19.2)	7.681 (18.0)	2.035 (3.8)	6.772 (11.9)	
Capan–ARIMA (1, 0, 0)	4.016 (5.6)	3.636 (8.0)	3.662 (5.9)	3.775 (7.4)	
Capan–ARIMA (1, 0, 0) x (1, 1, 2) 7	3.420 (4.2)	4.288 (9.8)	3.618 (6.2)	3.686 (7.3)	
Capan–ARIMA (2,1,4) x (1, 1, 2) 14	3.211 (3.9)	3.462 (7.8)	3.912 (6.7)	4.090 (8.1)	
Capan–linear regression	5.149 (7.5)	2.755 (5.9)	3.331 (6.3)	3.622 (7.1)	

ARIMA = autoregressive integrated moving average, RMSE = root mean square error, MAPE = mean absolute percentage error.
The mean RSME and MAPE are for days 1–7.

predicting LOS for patients who have already spent a long time in the ICU. One possible way to improve long-stay ICU LOS predictions is to develop an updating model that incorporates time-varying covariates, such as NEMS, which is commonly recorded daily. The implementation of time-varying covariates would allow the opportunity to improve the census forecasts most importantly as the planning horizon increases. Patient characteristics not present in our data set may have improved our forecasting model by allowing for the development of better-fitting survival models for patients in the ICU on the day of the census forecast. Finally, the data used to develop the algorithm was entirely collected before the COVID-19 pandemic. Future work will focus on making model adjustments to include factors related to the arrival rate and LOS of COVID-19 patients. The study described in the current paper will serve as a useful benchmark for comparison in future work.

CONCLUSIONS

The combination of ARIMA time series modeling and survival models of LOS enables forecasting of ICU census over short time horizons. This type of algorithm may be important to clinicians and managers when planning ICU capacity as well as staffing and surgical demand planning.

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