Medical Asset Management: Deep Learning Based Asset Usage Prediction in a Hospital Setting using Real Data

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***Abstract*—Periodic Automatic Replenishment (PAR) is an inventory management policy that assists the healthcare sector in keeping the right amount of stock on hand to avoid excess stock and the potential for products to expire. Traditionally, hospitals rely on the experience and firsthand knowledge of stock management technicians to keep their store supplies with enough equipment. However, manual management based on "gut feeling" and/or nursing feedback may lead to missing products or incorrect stock orders. Extracting accurate data is often too complex or time-consuming, resulting in a lack of critical reporting data to manage product inventories across the organization properly. However, adopting forecasting techniques and incorporating them into traditional PAR management policies can provide efficient solutions for controlling hospital warehouse inventory at the lowest cost. We have proposed a deep learning-based framework to monitor inventories to reduce costs and variation, create efficiencies, and improve the quality of patient care in hospitals. Furthermore, the proposed forecasting framework's performance is assessed using a real-world scenario within a hospital. The findings indicate that the system is capable of accurately tracking the usage of medical equipment, which results in a significant reduction in the unavailability of assets.**

***Index Terms*—hospital asset management, Internet of Things, deep learning, inventory management**

I. Introduction

IoT has been used for various applications and is becoming ubiquitous. Ranges of industrial, human, medical, and research applications employ IoT-based systems. Hospital asset management is one of the applications of IoT. In particular, IoT and Deep Learning (DL) can be used for inventory management in hospitals. Managing inventory in a hospital has complexity and high operational costs. This is due to expensive medical equipment being used and stored in multiple storage rooms within the hospital. And there is usage unpredictability of the medical devices [1]. In general, the healthcare sector has been facing various challenges in effectively managing these supplies for a long time. Lacking supplies and materials may postpone treatment and endanger patients' health whereas unused items or overstocking of supplies increases costs. Enhancing inventory management in hospitals such as supplies acquisition and movement across different locations while controlling costs requires coordination and integration between different fields such as manufacturing and operations research management to provide analytical methodologies, considering the limited human resources and supplies [2].

The goal of inventory management in hospitals is to assist in keeping the accurate recording of the inventory on hand to lower the out-of-stock rate of medical assets and eliminate overstocking and product expirations. In other words, balancing costs with the right amount of inventory considering complex and last-minute changes happening within the hospitals to ensure customer satisfaction is the biggest challenge that has caused poor inventory and distribution management in the hospital. Adopting forecasting techniques can help optimize stocking levels and thus sustain quality and timely patient care while efficiently utilizing expensive medical equipment.

Numerous strategies for managing inventory have been suggested, such as the two-bin Kanban system, reorder point/reorder quantity policy, reorder point/order-up-to policy, and periodic and continuous policies, [3]. The Periodic Automatic Replenishment (PAR) level system is frequently used to regulate inventory in aligning stock levels with the demand. PAR Levels refer to the minimum and maximum quantities set for a specific item, where the minimum level indicates the need for reordering when the quantity gets close to it. On the other hand, maximum levels indicate an excessive stock of an item, which may lead to wastage or expiration. A drawback of offline periodic solutions is that they only utilize the current inventory information disregarding historical information. This can lead to overstocking of some equipment or stock-outs. Furthermore, a continuous inventory system allows for continually updating the inventory on hand according to utilization data and capturing details that can improve patient care. For continuous replenishment systems, barcode and Radio Frequency Identification (RFID) tag-based strategies are commonly used due to no energy, inexpensive, and help automate the retrieval of information such as asset location and quantity [4]–[6]. This along with IoT and DL-based intelligent, real-time, and accurate decision-making systems is possible to improve productivity, patient safety, and lower costs.

In this paper, we design and develop an IoT and DL-based automated inventory management system for hospitals to ensure supply availability for scheduled medical procedures,

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up-to-date inventory information, and minimal clinical personnel involvement. In medical units, conventional inventory replenishment models establish both the timing of order (i.e., the reorder point) and the quantity to be ordered (i.e., the reorder quantity). These models often rely on experience-based inventory levels instead of data-driven actual inventory levels, resulting in an excess of units while others are in short supply. These approaches determine the reorder point and reorder quantity based on the current state of the inventory (i.e., available stock, used stock, and item's expiration dates). However, employing forecasting approaches helps predict the future inventory demand by considering demand variability and cost of ordering and thus improves inventory levels and logistics operations costs.

Our system design is based on a real-world hospital case where there are multiple inventories located at different departments within a hospital, holding different types of medical equipment. Each item is equipped with an ID and a BLE-based tag to manage its movement and type. Additionally, it records the time when an item is added to the inventory and when it exits the inventory. The major contributions of the paper are listed as follows:

- We design a framework that automates the asset tracking problem in a hospital environment using DL techniques.
- We combine DL models with Variational Mode Decomposition (VMD) method to accurately predict the medical asset availability in an inventory for different time horizons in the future.
- We evaluate our design through a real-world case study involving 29 clean storage zones (medical supply inventories) within a hospital. We selected the Central Supply Front (EDC) clean storage and focus our experiments on the four most frequently used categories.

The rest of this paper is organized as follows: Section II presents a literature review. Section III presents the asset tracking problem. Section IV outlines the system model along with the data preparation process and the prediction algorithms. Section V discusses the system's performance evaluation and Section VI concludes this work.

II. Literature Review

Duan *et al.* [7] proposed a metaheuristic-based simulation optimization framework to minimize the expected outdate rate under a predetermined fill rate constraint for supply chain inventory management of highly perishable products. They employed an age-based replenishment policy using an old inventory ratio that measures the freshness of the perishable products. They tested their approach for one blood center with three and six hospitals. Their inventory management policy helped reduce the system's expected outdate rate from 19.6% to 1.04% on average such that the demand and the supply are balanced. Rappold *et al.* [8] developed an analytic optimization framework to reduce inventory carrying and materials management costs in hospital environments. Their approach modeled the non-stationary stochastic demand and a stochastic bill of materials in surgical departments. Their results demonstrated great savings for hospital investment in inventory. Zwaida *et al.* [9] applied a deep reinforcement learning-based algorithm to address the drug inventory management problem in a hospital and minimize the drug refilling cost and shortage rate in real-time. Lee *et al.* [10] integrated RFID technique with neural network technology to automate and improve the efficiency of inventory management in hospitals. They deployed their proposed system integrated for tracking the movement and the usage patterns of the infusion pumps at a hospital. Their demand forecasting model for medical assets demonstrated that employing neural network technologies has several benefits such as reducing time spent on searching for medical devices, periodic maintenance, stock-take or locating of the lost devices, and releasing the medical staff from doing the paperwork. The work in [11] presented a comparative study of machine learning and classical statistical methods for demand forecast in a hospital setting. The objective of this study is to understand whether the application of statistical methods suffices to facilitate demand forecasting for an inventory management method in hospitals or whether employing machine learning algorithms can be invaluable. The study indicated that in an inventory management context, machine learning algorithms outperformed statistical approaches in terms of accuracy. Additionally, machine learning results can be influenced by time series characteristics as the results achieved by this work show machine learning has a high accuracy only on smooth and erratic time series. On the other hand, machine learning algorithms have larger execution times than statistical methods. Therefore, despite promising results from machine learning algorithms [12] to address medical shortages and inventory optimization we need to select the appropriate method with respect to the data characteristics. Nguyen *et al.* [13] reviewed and evaluated the scientific literature on the main benefits, opportunities, and challenges of data analytics-based pharmaceutical supply chains to enhance operational performance. Data analytics has proved to be a promising solution to improve pharmaceutical supply chain management. In particular, predictive techniques using machine learning algorithms provide accurate forecasts, thus contributing to tackling shortages and high inventory levels in a hospital environment. However, a few data resources have been extensively used so far. Additionally, there are various data types that need to be combined to ensure integrity and transparency in inventory management. Therefore, data analytics and artificial intelligence capabilities need to be investigated to address medical equipment shipping, distribution, and dispensing in inventory management as well as providing support in times of crisis such as the pandemic.

Although there have been research works that focus on designing and optimizing inventory and replenishment systems for hospitals, most of them either rely on statistical approaches or only a few utilize DL techniques to address drug shortages in hospitals. As far as our knowledge goes, no research has been conducted to specifically optimize the PAR inventory management policy while incorporating all types of medical devices and drugs available in a hospital inventory using DL approaches.

III. Problem Description

We aim to design an online solution that dynamically determines the future availability of medical equipment over a time span W while benefiting healthcare facilities using DL. Given a time series $T = \{t_1, \cdots, t_n\}$, each time step is associated with a number of available medical devices in the inventory. The time series consists of regularly spaced window time w in minutes. Our goal is to provide predictions within the time intervals as well as forecasting the minimum and maximum number of devices available for four different time horizons h in the future.

IV. System Model

A. Data Modeling-Time Series Analysis

Time series analysis is a fundamental component of data modeling. It involves leveraging insights from past observations to construct precise models capable of capturing the underlying structure of a series. These models, in turn, enable us to make predictions and categorize future events accurately. Researchers have dedicated considerable effort to developing more reliable and precise algorithms and models for time series data analytics. While the field of time series modeling has made remarkable strides, most of these models are designed to work with conventional time series data [15]. However, the challenge lies in the fact that raw data seldom conforms to the ideal scenario of having all input variables sampled at a consistent rate with synchronized timestamps across various variables. This irregularity arises due to the diverse range of sensing devices and recording techniques used to collect data. Transforming uneven data into an even dataset with fixed time intervals plays a pivotal role in enhancing the data's usability, consistency, and interpretability (e.g Fixed time intervals allow you to precisely associate predictions with the corresponding moments in the dataset). This transformation renders the data more suitable for a wide array of analytical tasks, including prediction and statistical analysis.

Unevenly spaced time series are usually examined after first converting data into evenly spaced observations through interpolation (generally linear). Yet, doing so can result in various important and difficult-to-quantify biases, particularly if the time between observations is excessively unpredictable

There are currently fewer methods specifically made for analyzing time series data with irregular spacing. To meet strict performance requirements, the least-squares spectrum analysis methods are frequently used. Yet, we will continue to use the re-sampling method due to its simplicity and low computational resource requirements.

B. IoT Infrastructure-Data Collection and Processing

In this section, we discuss the data collection and processing procedures for our IoT infrastructure in smart hospitals. The dataset we utilized comprises wireless data frames transmitted by CenTrak devices manufactured by CenTrak, as shown in Fig. 1 . These devices are strategically placed throughout the hospital environment, including rooms, corridors, and bays, to capture location information.

The CenTrak devices transmit a unique space identifier (e.g., room), which is received by any tag present in that space. The tags then communicate the space ID and their unique ID over existing Wi-Fi networks and/or CenTrak's specialized UHF network. This information is transmitted to a location server in real time, where it is delivered to the software application and other connected healthcare IT solutions.

We have two types of devices in our IoT infrastructure: virtual walls and monitors. Both types emit flashes of IR light that are read by the tags. Monitors are placed centrally on the ceiling of a room or area and flashlights are in all directions. On the other hand, virtual walls are designed with blinders, directing the flashlight downward from the device on one side of the vertical plane. Virtual wall devices are typically positioned near doors or other thresholds, capturing data about a tag's entry/exit without the need for extensive information beyond that.

In the specific context of measuring par levels, which include Clean and Soiled rooms, either type of device can be utilized. Approximately two-thirds of the rooms use monitors, while one-third use virtual walls. Monitors are centrally located on the ceiling, while virtual walls are placed near the door threshold on the interior of the room.

Our dataset was collected from several inventories across different departments within the hospital. It contains valuable information about the inventory, such as the type of medical device, the device ID/tag, the enter timestamp indicating when the device entered the inventory, the exit timestamp representing when the device left the inventory, the zone ID where the inventory is located, and the name of the inventory's location. However, it is important to note that noise can be introduced during the dataset collection process, resulting in inaccuracies in the proposed approach's performance.

One form of noise we identified in the collected data is the presence of short-time differences between the device's exit and entry timestamps in the inventory (e.g., 0, 1, and 5 seconds). Such occurrences imply that the device has been in use for only a very brief period, which is not logical in a hospital setting. To address this, we established an in-use minimum threshold (th) for all devices and removed all data points that fell within a time range of 0-th minutes. This process helps ensure the reliability of the data.

Next, we computed the number of remaining devices at the enter timestamp in the inventory for each category, taking into account their enter and exit times. This enabled us to construct another dataset with additional information, including the enter timestamp, device category, inventory location, and the number of remaining devices at the enter timestamp.

Furthermore, we did time series analysis as discussed in IV to transform the irregular time intervals (resulting from the unpredictability of entry and exit recording) . To facilitate

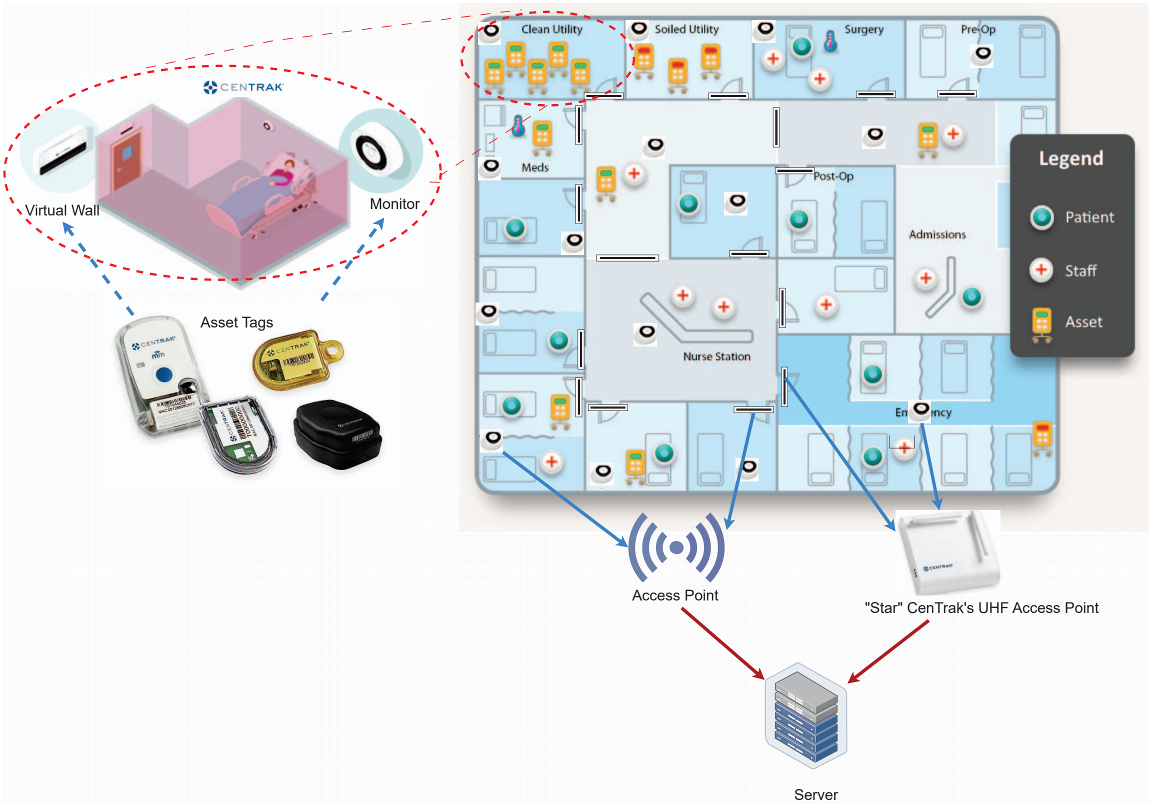


Fig. 1: IoT Infrastructure [14].

predictions within fixed-sized windows (e.g., hourly, daily, weekly, monthly, and annually), we transformed the data through resampling. Consequently, we created a new dataset with fixed observation intervals (w), providing a structured framework for measurements and facilitating the learning process.

C. Prediction Algorithms

We used multiple DL techniques for our forecasting framework such as Long short-term memory (LSTM), Gated recurrent unit (GRU), Convolutional Neural Networks (CNN), and Variational Mode Decomposition (VMD). Next, we briefly discuss them.

1) VMD: was proposed by Dragomiretskiy and Zosso [16] in 2014. VMD is an entirely non-recursive variational model [17] that concurrently decomposes a time series into K intrinsic mode functions (IMFs). Each IMF has a specific bandwidth in the spectral domain [18] and can be computed by solving the following convex optimization problem:

$$\begin{aligned} \underset{\{u_k\},\{\omega_k\}}{\text{minimize}} \quad & \textstyle\sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \\ \text{subject to} \quad & \textstyle\sum_{k=1}^{K} u_k = f \end{aligned} \quad (1)$$

where f is the input time series, t represents the time step, and $\delta(\cdot)$ denotes the Dirac delta function [19].

2) VMD-LSTM: refers to a combined approach that utilizes both VMD and LSTM techniques for analyzing and processing sequential data. The combination of VMD and LSTM, known as VMD-LSTM, aims to leverage the strengths of both techniques. VMD can be used as a preprocessing step to decompose the input data into its constituent IMFs. Each IMF can then be treated as a separate input sequence, and LSTM models can be trained on these individual components to capture their respective dynamics and patterns. By combining the decomposition capability of VMD and the sequential modeling capability of LSTM, VMD-LSTM can potentially provide improved analysis and prediction performance for complex sequential data.

3) VMD-GRU: is an integrated approach that combines VMD and GRU techniques to analyze and process sequential data effectively.

VMD-GRU takes advantage of the strengths of both VMD and GRU techniques. VMD is first utilized as a preprocessing step to decompose the input data into its constituent IMFs. Each IMF is then treated as an independent input sequence, allowing GRU models to be trained on these individual components. This approach enables the capture of distinctive dynamics and patterns within each IMF. By combining the decomposition capabilities of VMD with the sequential modeling abilities of GRU, VMD-GRU has the potential to significantly enhance the analysis and prediction performance for complex sequential data.

4) VMD-CNN: The VMD-CNN framework is a combination of two techniques: VMD and CNN. By combining VMD and CNN, the VMD-CNN framework likely leverages the strengths of both techniques. It may involve using VMD to decompose a time series signal into its constituent modes and then employing a CNN to process and analyze these modes further. CNNs have a good nonlinear mapping capability [20], and theoretically, they have been proven to be universal approximators that can estimate any nonlinear function to any desired accuracy [21]. The CNN could potentially learn discriminative features from the decomposed modes for tasks such as classification, prediction, or anomaly detection.

V. Experiment and Numerical Results

The proposed framework is evaluated using our real-world trial-generated dataset of medical equipment-IoT device interaction.

First, we describe the combination of DL models with the VMD method and the way it works in our experimental setup. As shown in Fig. 2, VMD decomposes the input time series into multiple IMFs. Next, each IMF is given to the CNN model for training. Then, each model generates its predicted signal. Finally, the predicted signals are summed to reconstruct the final prediction.

A. Case Study

Our case study environment is a hospital with 29 clean storage zones (medical supply inventories), each of which stores various types and quantities of medical equipment. Each clean zone is equipped with a sensing infrastructure of IoT devices that provide real-time location information about tracked medical equipment. The IoT network collects data as each piece of equipment enters or leaves the clean zone. Table I presents the specific parameter values utilized to assess our framework in this actual scenario.

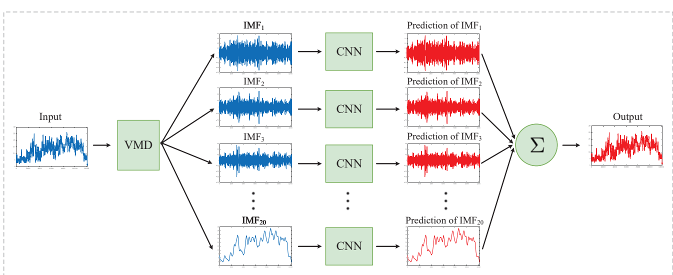


Fig. 2: Structure of VMD-CNN [19].

TABLE I: Case-Study Parameters

Parameter	Value
Device categories	Rental Bed, Asset Tag, Pulse Oximeter, Supply Cart
Window size (w)	$10, 20, 30, 60$ $minutes$
Range prediction horizon (h)	1 $hour, 1$ $week, 1$ $day, 1$ $month$
Device in-use minimum threshold (th)	5 $minutes$

B. System Evaluation and Overall Accuracy

In this study, the system's ability to predict the number of ready-to-use medical devices in the inventory was evaluated using a real-world-generated dataset. To assess this capability, four types of devices with the highest availability variation were chosen and analyzed using VMD-LSTM, VMD-GRU, and VMD-CNN models. An error analysis was performed using root mean square error (RMSE) and mean absolute percentage error (MAPE) metrics, and the results were compared across the models. The VMD-CNN model outperformed the VMD-LSTM and VMD-GRU models for all devices, except for the Rental Bed category, where the VMD-GRU model had an edge over the others.

Based on the overall better performance of the VMD-CNN model, it was selected, and the predicted values were visualized in relation to the target values for each device type. Figures 3a, 3b, 3c, and 3d show the plots for each device type, where the count of the device is plotted against the time step, with each time step referring to a 30-minute interval. The VMD-CNN model was able to closely match the target values for all devices.

The system was designed to perform several horizon lookaheads, including a one-step lookahead to mean 30 minutes in the future, 2-step, 48-step, 336-step, and 1440-step to show a 1-hour, 1-day, week, and month look ahead, respectively. For the plots in Figure 3a, a one-step lookahead was used to show how closely the model matches the target values. Additionally, the behavior and statistics of each device type were observed, such as the Asset tag device, which had a constant count or small step changes over time, with occasional variations. This tricky data distribution could have been missed in LSTM models due to the bias created for longer durations, but the CNN model was able to capture it.

In Figure 3b, it is evident that the data distribution and its nature fluctuate significantly, and this device type typically has poor error performance. However, the VMD-CNN model showed reasonable performance overall and performed better than the other models. The other two plots in Figures 3c and 3d had a data distribution that was intermediate between the two extreme distributions, and the system was able to perform well, closely matching the target values. These plots were also generated for a one-step horizon or one-step lookahead.

C. Range Prediction for Different Device Categories

In hospital asset management, it is important to accurately predict the availability of devices in the inventory. In a recent set of experiments, we used VMD-CNN to predict the minimum, maximum, and median number of devices available for different device categories and time horizons. As shown in Fig. 4, we were able to accurately predict the availability of the Pulse Oximeter device hourly, daily, and monthly (see Table II). When summarizing the predictions, it is useful to provide information about the spread of the data, which can be achieved by using the minimum and maximum values. The monthly availability range for the Pulse

TABLE II: Evaluation of combined DL models with VMD method forecasting performance.

Error Analysis									
Device	Model	Root Mean Square Deviation (RMSE)				Mean Absolute Percentage Error (MAPE)			
	Window Size	10	20	30	60	10	20	30	60
Asset-Tag	**VMD-CNN**	**0.0180**	**0.1006**	**0.0489**	**0.0537**	**0.2213**	**2.9624**	**1.0367**	**0.5202**
	VMD-GRU	0.2191	0.2587	0.2304	0.2549	4.8672	6.0714	4.7389	0.5283
	VMD-LSTM	0.2587	0.3618	0.3598	0.3950	6.0714	7.5021	7.2833	7.3841
Supply-Cart	**VMD-CNN**	**0.0562**	**0.0915**	**0.0903**	**0.1269**	**0.6753**	**1.5888**	**0.8037**	**1.1456**
	VMD-GRU	0.4914	0.4735	0.4699	0.5726	13.8513	13.0267	12.6215	15.1739
	VMD-LSTM	0.7976	0.7753	0.7592	0.8524	22.4840	21.5400	20.6915	22.6279
Pulse-Oximeter	**VMD-CNN**	**0.2213**	**0.3097**	**0.3692**	**0.4856**	**1.1862**	**1.7820**	**2.2640**	**2.8395**
	VMD-GRU	0.6937	0.8395	0.9618	1.1896	6.7061	7.5971	8.3315	10.8461
	VMD-LSTM	1.2650	1.3414	1.4560	1.7724	13.9395	14.2070	15.0476	18.1823
Rental-Bed	VMD-CNN	3.3939	3.5612	3.6968	1.5346	7.5626	7.8923	8.4118	4.2624
	VMD-GRU	**0.1863**	**0.2507**	**0.3034**	**0.4111**	**1.5511**	**1.8789**	**2.3796**	**3.5270**
	VMD-LSTM	0.6416	0.6996	0.7390	0.8006	9.7438	10.0180	10.2710	10.7511

Oximeter device, as shown in Fig. 4c, is an example of this. Additionally, when describing the central tendency of the data, the median is often a better measure to use when the data is not normally distributed or if there are outliers present. This is particularly relevant in hospital asset management, where outliers can heavily influence the data. To obtain minimum, maximum, and median values, we perform multiple iterations of the prediction process. After running multiple iterations, we aggregate the results to compute the minimum, maximum, and median number of available devices. The minimum represents the lowest availability observed among all iterations, while the maximum represents the highest availability. The median is calculated by listing and arranging the results of all the iterations in orderly manner and finding the middle value . Proceeding with the discussion, We omitted other devices' simulation results to conserve space. Fig. 4a illustrates the hourly prediction for three consecutive days in February 2022. The first day is Saturday starting from noon to 11 PM showing Pulse Oximeter will be available at its maximum at noon and then the availability decreases to a single device at night. On the second day of the weekend, Sunday, there is a larger time window of data points where the availability is the same as the previous day meaning that the hospital staff are not going to use the device. On the third day, Monday, which is Presidents' Day, when federal employees get the day off, the model forecasts the availability of the device will increase and remain the same all day except for the evening when it will be required perhaps due to an emergency situation (e.g., it could be a COVID patient who needs to measure their blood oxygen level).

Fig. 4b demonstrates the daily predictions. As shown in the figure, each stick is associated with a day forecasting the minimum and maximum number of available devices within the inventory throughout that day. Fig. 4c shows the device availability flow monthly where in the last month of the year 2020 the device availability range is at the lowest amount implying that the demand for Pulse Oximeter in the hospital is high, whereas, throughout the year 2021, the availability fluctuates and reaches its peak showing the demand for this device is not as high. In early 2022, Combining DL the availability decreases and reaches its minimum.

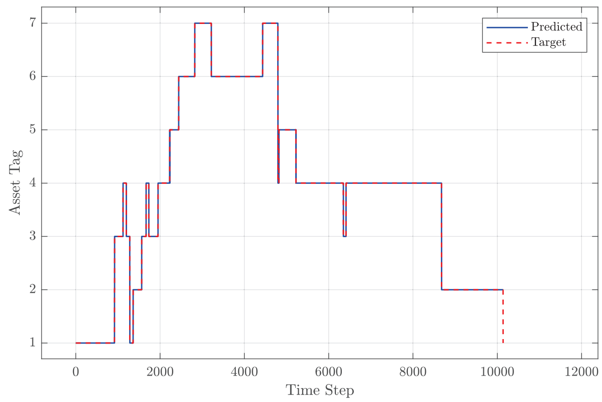
D. Impact of Combining DL models with VMD

Finally, we examined the impact of incorporating VMD into the DL algorithms performance. The outcome is illustrated in Fig. 5. From the top figure, we can observe that the majority of device categories have profited from the combined approach and achieved higher performance except for Supply Cart. Additionally, the combined approach in the bottom figure shows better performance than the regular DL algorithm for all categories. This behavior is attested to the fact that the combined approach can help achieve better accuracy for the system.

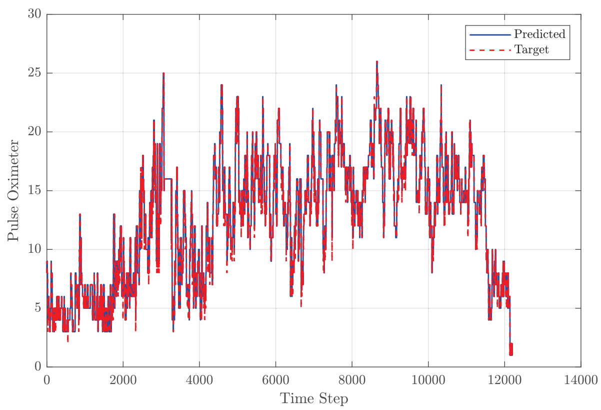
VI. Conclusions

Unfortunately, most of the inventory management tasks are carried by healthcare workers manually requiring training process and collaboration with vendors, align with hospital staff such as physicians and nurses imposing a burden on the workers. Automating the current hospital inventory management systems possesses multiple advantages such as releasing staff from logistics tasks, reducing the risks to improve the patient safety, eliminating the need for designing complex work flow systems, and processing a large amount of data to come up with an efficient state of inventory management.

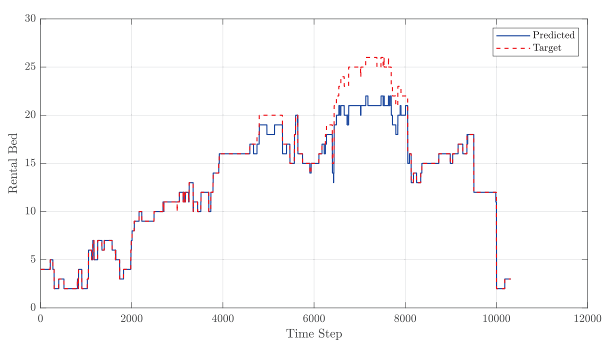
In this paper, we proposed a DL-based framework that automates the tracking process of supply consumption and notifies the personnel to adjust the inventory levels. We used



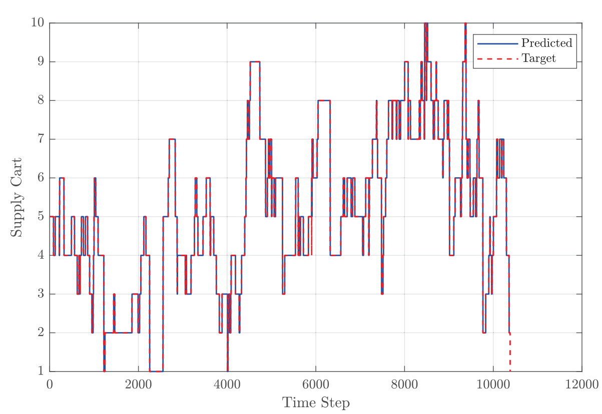
a Asset Tag count forecasting



b Pulse oximeter count forecasting

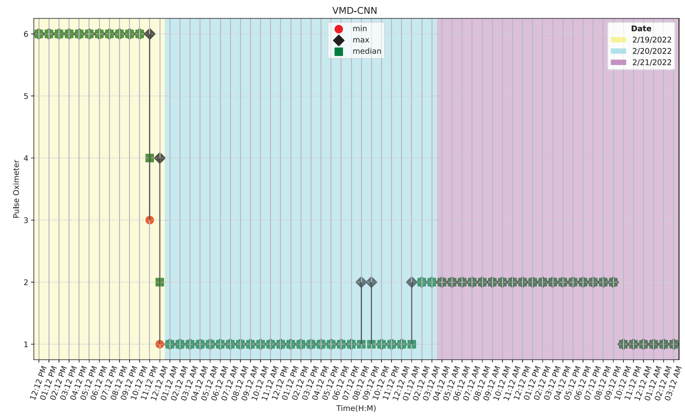


c Rental bed count forecasting

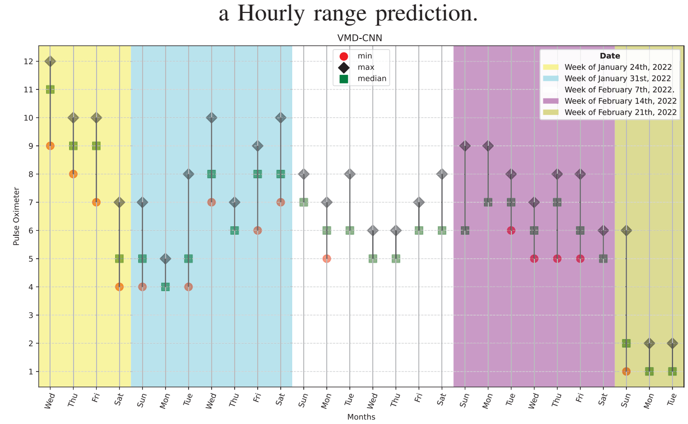


d Supply cart count forecasting

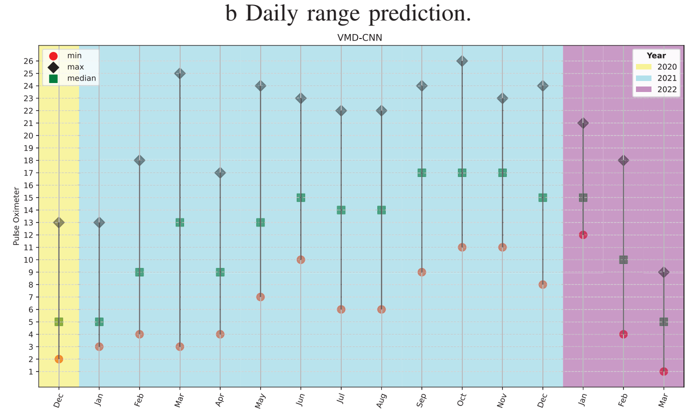
Fig. 3: Device count evolution over time step using VMD-CNN: predicted vs target values for different devices.



a Hourly range prediction.



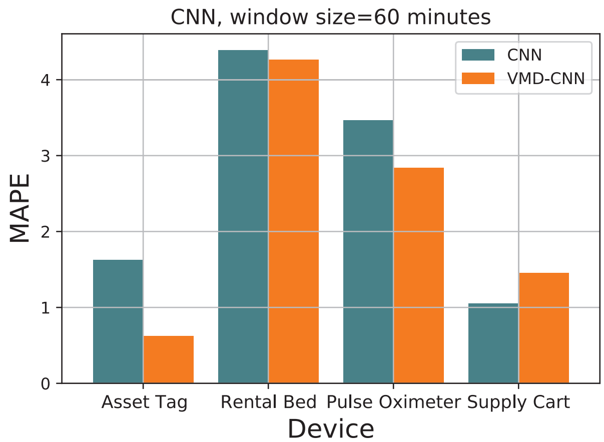
b Daily range prediction.



c Monthly range prediction.

Fig. 4: Pulse Oximeter range prediction for different time horizons using VMD-CNN.

three DL models and their combination with VMD method to enhance the prediction accuracy using a real-world dataset. The VMD-CNN approach achieved the highest accuracy in comparison to other approaches. Our experimental results indicate that our design can substantially help monitor the medical asset usage accurately, whether used as a standalone system or in conjunction with other asset tracking tools. This study is replicable because it does not include sensitive data covered by HIPAA. While customers of this solution can



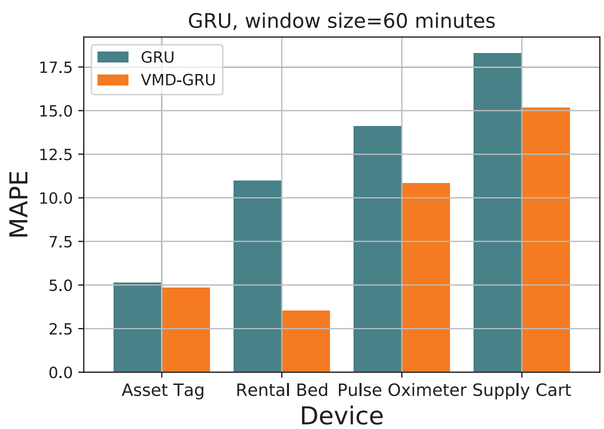


Fig. 5: Accuracy comparison for combined CNN (top) and GRU (bottom) approaches.

securely store and communicate Protected Health Information in a limited manner, that data was explicitly excluded from this study and can easily be parsed out in future studies if it is present.

VII. Acknowledgments

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