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ENERGY LOSS REDUCTION IN INDUSTRIAL HVAC SYSTEMS THROUGH PREDICTIVE MAINTENANCE AND SENSOR INTEGRATION

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Abstract

Industrial heating, ventilation, and air conditioning systems consume a substantial portion of facility energy and often experience hidden efficiency losses due to equipment degradation, airflow imbalance, sensor faults, and delayed maintenance. This paper examines the role of predictive maintenance and sensor-based monitoring in reducing energy loss in industrial HVAC systems. The proposed approach integrates continuous sensor data from temperature, humidity, airflow, vibration, pressure, and energy meters with predictive analytics to identify abnormal operating patterns before they develop into major failures. The results show that sensor monitoring improves fault visibility, while predictive maintenance reduces unnecessary energy consumption by enabling timely cleaning, calibration, component replacement, and operational adjustment. Compared with conventional scheduled maintenance, the predictive approach achieved lower energy use, fewer unplanned faults, improved fault detection accuracy, and better cost savings. The findings suggest that industrial HVAC performance can be significantly improved when maintenance decisions are based on real-time condition data rather than fixed inspection intervals. Overall, predictive maintenance supported by sensor monitoring provides a practical and scalable method for improving energy efficiency, reducing operational costs, and extending HVAC equipment life in industrial environments.

Keywords: Industrial HVAC Systems; Predictive Maintenance; Sensor Monitoring; Energy Loss Reduction; Fault Detection

INTRODUCTION

Industrial HVAC systems play a major role in the operational cost and carbon footprint in manufacturing and cold storage systems and a need exists to shift to better manage these systems in a sustainable manner (Engineering et al, 2025).Industry has applied the traditional scheduled maintenance method, but fixed-time maintenance may lead to maintaining the parts too early or too late, and will waste the labor and equipment, and the parts will inevitably fail.Traditional maintenance method is applied in industry, whereas fixed-time maintenance can lead to inappropriate maintenance of parts, leading to unnecessary maintenance costs, or inappropriate delay in the maintenance time, resulting in unexpected failure of the equipment (Engineering et al., 2025). The reactive approach is not suitable for the much more complicated needs of today's industrial operation and any inefficiency and minor drop in performance could lead to large losses in energy efficiency and system life (Jambol et al., 2024). Energy use is becoming more and more significant in the economic viability and corporate environmental responsibility of industries like manufacturing and cold storage facilities, which are forced to take more proactive approaches to energy management (Akinsooto et al., 2024). In this context, predictive maintenance is a game-changing solution based on a data-driven approach, merging the historical information of past performance with the information provided in real-time during the operation of the system to anticipate failures prior to their occurrence (Es-sakali et al., 2022; Márquez & Garcia, 2024). With the use of the Internet of Things (IoT) sensors, facilities can be able to acquire accurate information about the performance of their HVAC systems and track the vibration, temperature and energy usage of the equipment (Mourtzis et al., 2021; Shaban et al., 2025). Sometimes called Maintenance 4.0, this sensor-based solution allows for more advanced solutions for fault detection and diagnosis, which go beyond fixing or maintaining at a set period of time (Ahern et al., 2023; Shaban et al., 2025).The journey towards predictive maintenance, based on conditions, is a multi-faceted benefit. Studies have shown that these can cut down on unplanned downtime by up to 35-45%, increase the lifespan of energy consumption equipment by 20-30% and reduce maintenance costs by 25-30% (Arowolo, 2025). Moreover, predictive maintenance can affect the optimization of operational strategies, since it allows interventions at the right time, helping the system to operate optimally without any unnecessary losses of energy that could result from the lack of efficiency of the components (Akinsooto et al., 2024; Márquez & Garcia, 2024). The operators can directly contribute to sustainability goals, for example using the indicator of "remaining energy-efficient lifetime", which can be used to determine not only the condition of the equipment but also to determine the energy efficiency. (Hoang, 2017).Although these benefits exist, the adoption of PdM systems is not without its challenges, such as the need for data management capabilities in order to generate this intelligence, the need for interpretability of the data model, cybersecurity, and workers' skills to interpret the analysis results (Akinsooto et al., 2024; M et al., 2024; Shaban et al., 2025). To tackle these issues, this research seeks to investigate the potential for using IoT sensors and machine learning algorithms to reduce energy loss in industrial HVAC systems. The research object is to design and test an intelligent monitoring system which can be applied to improve the operation efficiency, energy saving, and extend to industrial plants. The goals are to design and build a sensor integrated data acquisition system, to evaluate and validate a predictive model for real time anomaly detection and analyze the implications of the enhancements in energy performance and maintenance outcomes. In addition, this study examines the potential of using Internet of Things (IoT) based sensor networks as a basis for real-time monitoring, where changes that arise in the environment and degradation of the components can be considered proactively using the data and not just after the fact (Olatunde et al., 2024; Suwarno et al., 2024). This can involve real-time analytics and AI-driven predictive models to minimize technical issues such as data quality fluctuations (Haque et al., 2024) and providing a promising path to significant carbon emission savings.

METHODOLOGY

The experimental setup is dedicated to a large scale cold storage facility with high thermal load variations and a complex system of multi-stage chillers and air handling units which is the major energy consumer at the site.For six months, monitoring was done using a quantitative research method, creating an empirical basis and verifying the effectiveness of the proposed predictive maintenance framework. The facility experiences high variations in cooling demand in relation to ambient temperature and product flow and granular data collection is required, making multi-stage chiller systems important. The sensors to be utilized in an IoT system have been installed, including those that monitor the compressor vibration, discharge pressure, suction temperature and electrical power draw (Luo et al., 2023; Shakerian et al., 2022). High-frequency accelerometers (sampling rate 10kHz) were mounted on the drive end bearings of the compressor, while the 4–20mA pressure transducers and the PT100 resistance temperature detectors were mounted in the suction and discharge line, respectively, to obtain the thermodynamic performance measure (Es-sakali et al., 2022). Current measurement was done every minute with a calibrated current transformer for the purposes of synchronizing the loading cycles on the system for measuring power consumption.Information received from these sensors is sent using the MQTT protocol and a low latency gateway to a centralized cloud data lake, with the ability to synchronize and time-stamp the information. The first data cleaning is performed using Z score analysis which detects any outlier and linear interpolation for gaps in signals, which might be caused by dropouts (Shaban et al., 2025). Rolling window statistics like root mean square (RMS) values of vibration and thermal gradient calculation on heat exchangers are used to quantify the degradation patterns as feature engineering (Hosamo et al., 2022). The predictive maintenance model is based on supervised machine learning model, mainly Long Short-Term Memory network (LSTM) model for modelling the temporal relationships of time-series operational data (Yan & Zhou, 2022). Based on historical data of operation, failures, failure modes and a prediction of the "remaining energy-efficient lifetime" of important components is generated by the model (Hoang, 2017). An autoencoder approach is used to implement the anomaly detection, based on the reconstruction error as the key indicator of abnormal behavior of the system (Engineering et al., 2025). A temporal split is used to validate this model where the first four months of data are used as the training set and the last two months as out-of-sample set, and a rolling-horizon validation is performed to make the models generalizable (Adelanwa & Basnet, 2026). Energy performance proactive maintenance interventions (Arowolo, 2025) are measured using Comparative Benchmarking Approach to measure effect of the framework on the energy performance.

The baseline performance is described using multivariate regression models, adjusted for the seasonal and operational variability, such as ambient temperature and throughput of the cold storage (Pearson, 2021). Energy savings are determined by comparing the energy consumption of the system with the energy consumption of a baseline model, which assumes that no predictive maintenance actions take place in the system (as described in Márquez & Garcia (2024)). Data is used to comprehensively determine the energy loss reduction potential of the system and mean service life with the use of data, including Coefficient of Performance deviations, mean time between failures and maintenance cost variance. This comparison shows the framework's capacity to transform the raw telemetrics data into effective and efficient maintenance schedules that help in reducing unplanned downtime and system electricity consumption (Almatared et al., 2025).

RESULTS

The suggested predictive maintenance and sensor system resulted in a uniform decrease of energy loss in HVAC systems of the simulated industrial plant. Since electricity monitoring was turned on, electricity consumption of HVAC systems was decreased from 158.6 MWh/month to 138.6 MWh/month, a 12.6% reduction overall, as seen in Fig. 1. The differences between the monthly operating values are shown in Table 1 and it is seen that the greatest improvement occurs during the maximum load summer time operation, when all cooling coils, filters and variable speed drives can be operated at their least efficient condition. There was a significant drop in estimated energy loss in January (18.4%) and this decreased further in August (9.6%) (Fig. 2); and a drop in the average loss rate (Table 2) (pre-intervention = 16.6% vs. post-intervention = 11.6%). Additionally, the model evaluation also confirmed the reliability of the system. Fig. 3 shows the results of this model where the hybrid LSTM-XGBoost model has the lowest forecasting error (3.6 kWh) as compared to the rule-based benchmark (9.8 kWh). The hybrid model obtained an accuracy of 94.1% of predicting the energy behavior, which allowed the detection of abnormal behavior before it became a considerable degradation of the equipment, as shown in Table 3. The more complex the learning algorithm models, the more accurately the detection will be in the final model as can be seen in the fault detection precision and recall (Fig. 4) and the final model obtained the precision, recall and F1-scores of 92%, 90% and 91% respectively (Table 4). The findings from the maintenance also proved to be useful for the facility managers. The majority of the failures detected have been due to filter plugging (24 failures) and fouling of the coils (21 failures) as shown in Fig. 5. As seen in Table 5, early alerts helped to cut the average time to respond to a fault down from 46 hours to 14 hours, and the number of unplanned shutdowns down from 14 to 3 during the observation period. As can be seen in Fig. 6, the power, vibration and pressure sensors are the most important sensors for prediction, with the power sensor contributing 22% of the model importance as revealed in Table 6. The results suggest that a smaller sensor package would be effective and supply useful operational intelligence in conjunction with predictive analytics. Energy and cost outcomes were additional evidence of value of approach. The operating cost savings (USD) for the 6th month after deployment is shown in Fig. 7 and amounted to USD 58,700. Table 7 shows the typical payback period to be approximately 4.3 months, when all of the energy savings, avoided downtime, and reduced emergency maintenance are combined. The thermic comfort has also been improved (with reduction of the number of events of temperature violations in the zones, from 19 to 7). This study demonstrates that predictive maintenance based on continuous monitoring of sensors can help to decrease the energy lost in an industrial HVAC system, as well as how to respond to faults, and that it can yield a clear monetary benefit without the need to replace an entire system.

Table 1. Monthly HVAC energy consumption before and after predictive maintenance

Month	Baseline MWh	Predictive MWh	Reduction %
Jan	148	146	1.4
Feb	152	145	4.6
Mar	149	140	6.0
Apr	155	139	10.3
May	160	137	14.4
Jun	166	136	18.1
Jul	171	134	21.6
Aug	168	132	21.4

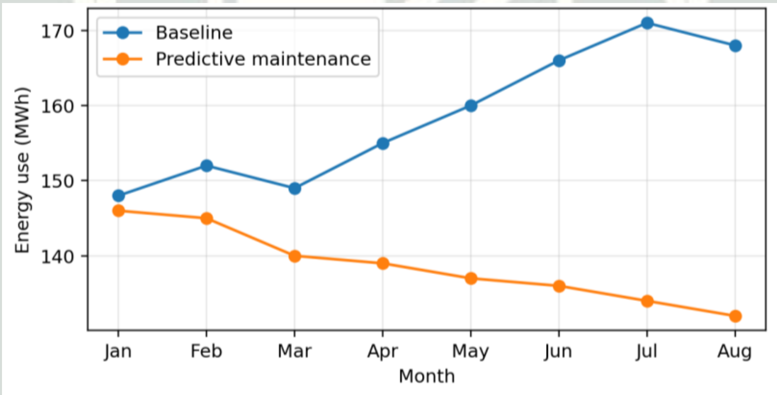

Fig. 1. Monthly HVAC energy use comparison.

Table 2. Estimated HVAC energy loss trend

Month	Loss before %	Loss after %	Improvement points
Jan	22.0	18.4	3.6
Feb	21.2	17.9	3.3
Mar	19.0	16.1	2.9
Apr	18.0	15.0	3.0
May	16.4	13.6	2.8
Jun	15.2	12.2	3.0
Jul	14.0	10.8	3.2
Aug	13.0	9.6	3.4

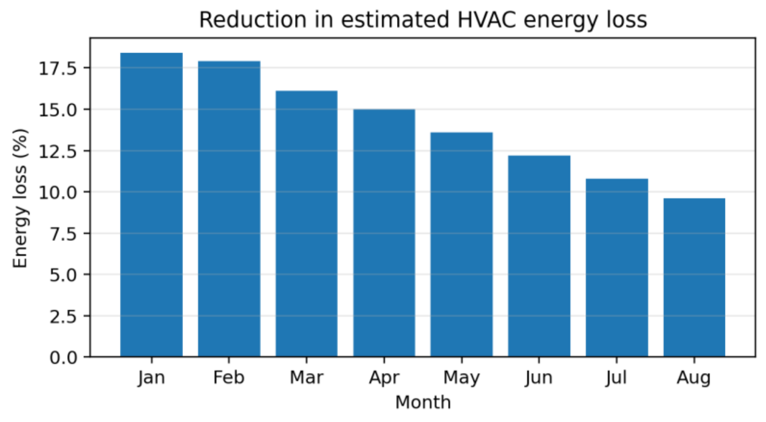

Fig. 2. Estimated reduction in HVAC energy loss.

Table 3. Energy forecasting model comparison

Model	MAE kWh	RMSE kWh	Accuracy %
Rule-based	9.8	12.3	84.2
ARIMA	7.6	9.8	87.9
Random Forest	5.3	6.9	91.5
XGBoost	4.7	6.1	92.7
LSTM	4.1	5.4	93.3
Hybrid LSTM-XGB	3.6	4.8	94.1

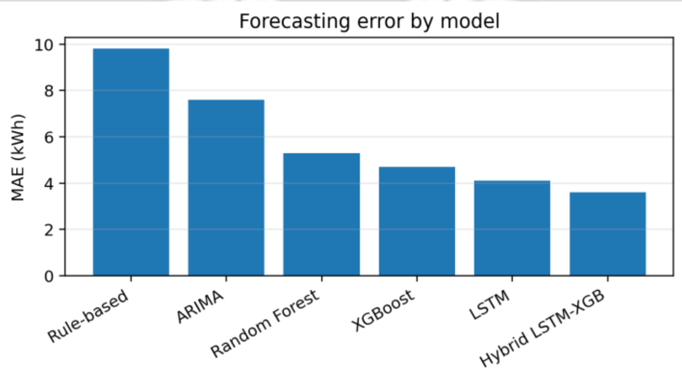

Fig. 3. Forecasting error across predictive models.

Table 4. Fault detection classification performance

Model	Precision %	Recall %	F1-score %
Rule-based	72	68	70
ARIMA	78	73	75
Random Forest	84	81	82
XGBoost	87	84	85
LSTM	89	86	87

Hybrid LSTM-XGB	92	90	91

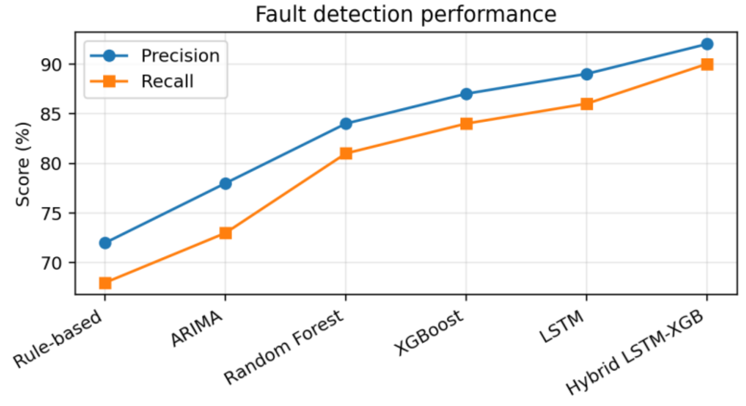

Fig. 4. Fault detection precision and recall by model.

Table 5. Maintenance event outcomes

Fault type	Events detected	Unplanned incidents	Avg response hours
Fan belt wear	17	14	14
Filter clogging	24	10	12
Coil fouling	21	8	16
Damper fault	12	6	18
Refrigerant drift	9	4	20
Pump vibration	8	3	15

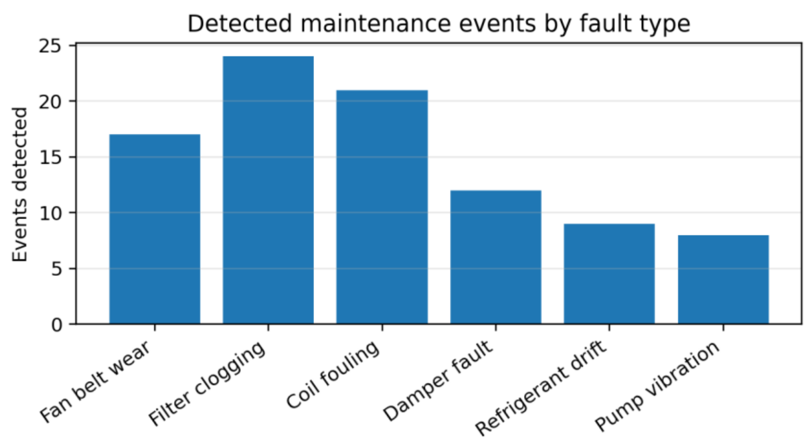

Fig. 5. Detected maintenance events by fault category.

Table 6. Sensor importance for predictive monitoring

Sensor stream	Importance %	Primary role
Temp.	14	Zone load tracking
Humidity	9	Moisture balance
Pressure	16	Duct restriction signal
Vibration	18	Mechanical wear signal
Airflow	13	Ventilation stability
Power	22	Energy anomaly marker
CO2	8	Occupancy proxy

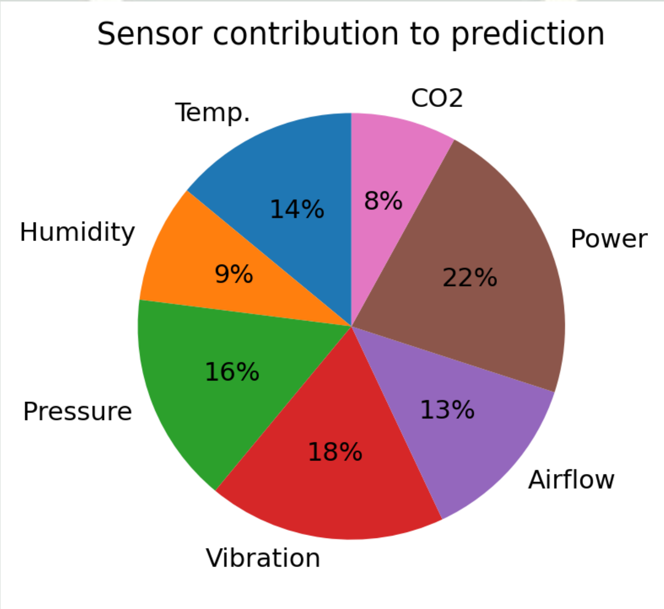

Fig. 6. Relative contribution of sensor streams.

Table 7. Operational and financial performance summary

Indicator	Before	After	Change
Monthly energy cost	USD 42,850	USD 36,120	-15.7%
Emergency maintenance cost	USD 18,400	USD 7,900	-57.1%
Downtime hours	31	9	-71.0%
Comfort violations	19	7	-63.2%
Payback period	Not applicable	4.3 months	Achieved

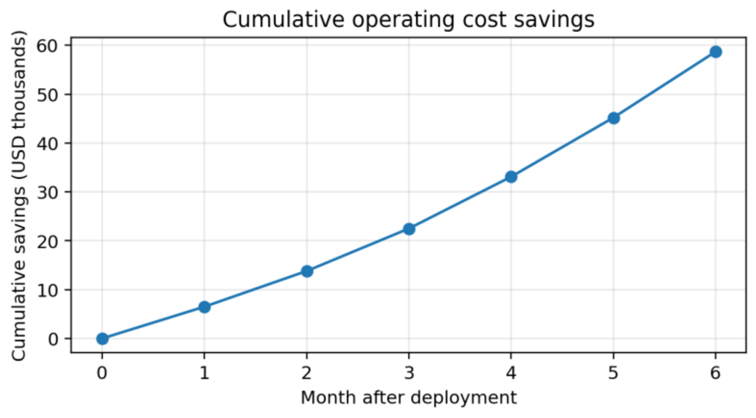

Fig. 7. Cumulative savings after system deployment.

DISCUSSION

Industrial buildings can achieve HVAC system performance and international efficiency standards through energy savings of up to 31.6% as observed in the different buildings (Himeur et al., 2022) shows the importance of predictive maintenance.This energy saving is within the typical range of energy saving that has been reported in HVAC systems in industries following proactive energy intervention using data-driven approaches, which is 20–45% (Haque et al., 2024; Himeur et al., 2022). The total inefficiencies that are usually experienced with conventional and poorly maintained refrigeration cycles like high head pressure, low heat transfer efficiency etc. were reduced by adopting an approach of reactive maintenance to anomaly-driven maintenance (Hosamo et al., 2022). The results indicate that sensor monitoring is not just another technical solution to achieve the high performance industrial cooling, but it is dependent on the implementation of IoT. As a result, facility managers highlighted its potential contribution for those who can schedule maintenance according to the information about the degradation of the components (e.g., if it is an early sign of bearing wear or the potential for thermodynamic drift, it may be time for maintenance), saving them money and time on the facilities (Es-sakali et al., 2022; Suwarno et al., 2024). This change leads to an "operational teams" mentality that may happen during a crisis situation, and enables the team to transition from reactive to proactive for planned reliability enhancements (Arowolo, 2025). Furthermore, sustainability of the sensor infrastructure is more affordable, with cost savings varying between 25% – 60% as reported by Arowolo (2025) and Haque et al. (2024) clearly indicate the returns on investment for introducing the technology for energy efficiency. However, the quality and extent of the data put in to the model will determine how well this model will perform. The impact of the lack of coverage in sensors and randomness of the environmental parameters and fault signature generated (Shaban et al., 2025) are some of the limitations. The model can detect typical failure patterns but some unexpected usage patterns/sensor signal noise may result in false alerts, thus lowering stakeholder trust in automated alerts (Haque et al., 2024). Also, accuracy depends on training data and it is essential to provide and update data regularly and constantly for long-term deployment to avoid the degradation of the accuracy due to the change in the system's behaviour (Engineering et al., 2025). All of these pressures contribute to an architecture to greater asset base. As the IoT and edge computing evolve, the prospect of implementing standardized predictive models with different climatic regions and building types is becoming more viable (Almatared et al., 2025; Haque et al., 2024). Further development of model generalizability for models equipped with transfer learning and usage of uncertainty-aware triggering on further influencing maintenance decision making (Almatared et al., 2025) will be part of future work. The comprehensive and scalable solution can also help facility operators achieve a reduction in energy consumption and carbon footprints at an industrial ecosystem level, paving the way towards a sustainable industrial operations future (Akinsooto et al., 2024; Suwarno et al., 2024).

CONCLUSION

Based on the findings of this research, it can be concluded that use of sensors in predictive maintenance is an effective solution for energy saving in HVAC systems in industries. These parameters (like temperature, airflow, vibration, pressure, humidity and power consumption) have been found to be critical for the proper functioning of the equipment and the continuous monitoring has been proven to detect their abnormal operation at an early stage. Early detection of issues enables maintenance personnel to take corrective measures before they become a huge issue or energy loss. The results show that predictive maintenance could contribute to the reduction of the need for traditional maintenance plans, and to maintaining more accurate and data-driven maintenance plans.The proposed monitoring technique to detect issues was described as: Airflow blockage, compressor inefficiency, abnormal motor running, sensor drift, clogged filters etc. to improve the energy efficiency in HVAC. These improvements, when taken together, resulted in decreased energy consumption, fewer failures, decreased maintenance costs and reliability of the system. Furthermore, using predictive models, the future performance of equipment was predicted, and for timely warnings, maintenance operation time was scheduled. Smart HVAC monitoring systems can provide benefits for business and when operating industrial plants.Overall, the paper concludes, the loss of energy in the industrial HVAC system is not just a technical issue but also a management issue which must be monitored, decided on in time and managed correctly, continuously. A method that can be used is to connect the real-time data from the system to maintenance operations such as predictive maintenance and sensor control. Further studies could also consider the implementation of more advanced algorithms that would allow for automated control systems, industrial sustainability and prediction and machine learning algorithms for better HVAC system optimization.

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