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Improving Outdoor Unit Efficiency of Air-Conditioning Systems in Hot Climates Using Artificial Intelligence

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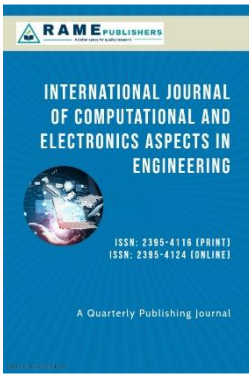

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Abstract. Air-conditioning (AC) systems in high temperature environments suffer serious performance loss as the surrounding temperature raises the ambient temperature, thereby decreasing the ability to reject heat by the condenser and requiring more compressor energy. This issue is acute especially in areas like in Iraq where the outdoor temperatures in summer often go beyond 45 degrees C, resulting in poor cooling performance and higher demand of electrical energy and mechanical stress on the outdoor unit components. The current paper suggests an artificial intelligence (AI)-assisted performance improvement system of air-conditioning outdoor units in the conditions of high ambient temperature. A thermodynamic and mechanical model of work cycle vapor-compression refrigeration is constructed to examine the system characteristics when the ambient temperatures vary under various profiles. The AI module is proposed as a rule of thumb optimization tool to improve the operating parameters of the outdoor unit such as condenser fan speed and compressor loading to achieve consistent operation and enhance the effectiveness of heat rejection. The simulation outcomes of the vast variety of ambient temperature conditions indicate that the suggested method is more effective in terms of the overall coefficient of performance (COP), compressor power usage, and lowering the temperature of the condenser than the traditional fixed-parameter control. The results suggest that the introduction of AI-based adaptive control into the current air-conditioning systems may become a viable solution to improving the energy efficiency and reliability of the systems in the hottest climatic conditions without necessarily changing the hardware significantly.

Keywords: Air-conditioning system; Outdoor unit; Hot climate; High ambient temperature; Condensing unit; Artificial intelligence; Energy efficiency.

1. Introduction

The performance of air-conditioning (AC) systems in hot climates is evidently reduced as the ambient temperature of the surroundings of the outdoor condensing unit is high. In very hot climates like Iraq, where ambient temperature in summer often goes over 45 C, the cooling off ability of the condenser reduces and the compressor must run with a higher condensing-pressure, which decreases COP and raises electrical power usage. This action is consistent with the thermodynamic activity of the vapor-compression systems and has been pointed out in the recent literature on HVAC that has been dedicated to the hot-weather operation and efficiency problems. Moreover, the degradation of performance under high ambient temperature exposes the outdoor unit to all sorts of thermal and mechanical stress that hastens failures, deteriorates operational reliability. Recent reviews are sure that HVAC performance and energy efficiency may be highly influenced by environmental disturbances and demand better control/optimization strategies, particularly in the climates with extreme weather conditions [1].

The conventional mechanical methods to better the performance of outdoor units on hot climates involve primarily augmenting the heat transfer of the condenser side using a greater condenser surface area, enhanced fin-and-tube arrangements, microchannel heat exchangers or a more effective arrangement of the airflow. Variable-speed condenser fan is particularly attractive in the sense that it can be introduced to provide greater performance of the system at high ambient temperatures without altering the refrigeration loop and can be modified to meet the already available outdoor units. In a case study, Catrini et al. studied the air-cooled chillers with variable-speed condenser fans that revealed that sophisticated fan control systems can use less energy at various operating conditions than constant-speed operation [2]. Most traditional approaches to control, however, are still based upon fixed condensing set points or simplistic rule-based logic, which might not provide the best heat rejection characteristics at elevated ambient temperature change.

Artificial Intelligence has been becoming an auxiliary optimization-control aid in the field of HVAC engineering to overcome the shortcomings of fixed-parameter control. This direction does not eliminate the thermodynamic model, but merely offers an overlay which has the potential to learn nonlinear correlations between environmental inputs (e.g. ambient temperature) and system performance outputs (e.g. COP and compressor power). The review by Zhou et al. confirmed the high capabilities of machine learning methods to HVAC optimization and control particularly in cases where systems dynamics are nonlinear, and classical controllers are unable to respond effectively [3]. Likewise, the literature demonstrates that the HVAC operation can be optimized by AI-assisted controllers in real time and respond to energy performance when paired with physically meaningful system constraints [1].

Although there has been a lot of research on AI in HVAC, the majority of the studies deal with building-level indoor comfort control or large-scale plant control, whereas less studies discuss the actual mechanical performance issue at the outdoor unit level under extreme high ambient temperature. It is a key deficiency to Iraq since the efficiency reduction and failures are frequent caused by restrictions of the condenser heat rejection instead of thermal comfort indoors. Recent studies have shown that model predictive control (MPC) models that use data to predict can lead to the realization of air-conditioning energy efficiency to a large extent, by learning to predict in conjunction with optimization [4]. Moreover, Huang et al. emphasized that the effectiveness of MPC is highly reliant on formulation and constraint tuning, which is particularly critical in case of extreme operational pressure (thunderous weather conditions) like hot weather [5]. Consequently, additional mechanical experiments using simulations would be necessary to determine the magnitude of the potential of AI-based supervisory optimization to improve COP, minimise compressor power, and stabilize condenser thermal behaviour in particular to outdoor units with extreme heat.

The rest of this paper is structured in the following way. Section 2 shows the description of the system and thermodynamic/mechanical modeling of the vapor-compression air-conditioning cycle with a focus on the heat rejection properties in outdoor units. Section 3 creates the high-ambient-temperature performance degradation issue and outlines the measures of evaluation. Section 4 outlines the AI-aided supervisory optimization concept and its incorporation to the outdoor unit mechanical model. Section 5 outlines the simulation procedure, scenarios and working conditions simulating Iraqi summer weather. The results of performance comparison between the proposed AI-assisted approach and the conventional one used as a baseline are introduced and discussed in Section 6. At last, Section 7 summarizes the work and gives viable suggestions towards real-world hot-climate deployment and future study interests.

2. Related Work

The high ambient temperature operation has been commonly identified as one of the serious constraints of the traditional vapor-compression air-conditioning systems, especially on residential and split-type units that are served by air-cooled condensers [6-10]. In hot climates the ambient temperature rises, resulting in high condensing pressure and lowering the heat rejection efficiency which results in lower cooling capacity and decreased COP [36-38]. A focused review of the residential air conditioning systems that are run under the conditions of high ambient temperatures highlighted that the reduction in the performance of the system in the aforementioned environment is dominated by restrictions on the condenser side as well as the increase in compressor work load that prompts the necessity of improved strategies of running the outdoor unit in the high ambient temperature conditions [11]. Moreover, recent research studies covering the operation of the hot-climate AC system in its entirety emphasize that the higher the ambient temperature, the greater the energy demand and lower the efficiency of the system, particularly in the peak summer seasons [12].

A variety of mechanical solutions have been suggested to reduce the effect of performance degradation with extreme heat, and much attention is paid to enhancing the heat rejection at the condenser side. A typical approach that has been investigated is condenser air pre-cooling (adiabatic or evaporative pre-cooling), which includes the reduction of the inlet air temperature and increases the condenser heat transfer. Recent laboratory results have established that adiabatic pre-cooling can be incorporated into residential air-conditioning systems and that cooling performance and energy efficiency when operating under hot conditions are quantitatively enhanced [13]. On the same note, recent journal literature on evaporative cooling schemes to split-type systems has shown an increase in COP and compressor power consumption due to increased condenser heat rejection, but these techniques have been associated with feasibility issues of water supply, size, and maintenance [14].

The next line of research is to enhance the management of the airflow and operations of components through the regulation of the operating conditions of the condenser fans and system. Mechanical analyses indicate that under high condenser fan-speed strategies have the potential of lessening energy use and enhancing operational stability over operation at fixed fan-speed, especially with changing thermal loads and disturbances in the ambient conditions [15]. Moreover, the study of the design of HVAC condensers proves that optimization of condenser and airflow conditions is highly essential in reaching the desired energy-saving performance not only in the high-temperature and humid climate but also in the extreme conditions of thermal stress of an outdoor unit [16]. Most of these mechanical refinements despite being effective, rely on fixed cycles or hard-tuning and are not usually tuned to suit different weather conditions in an optimum way.

Over the past few years, data-driven and AI-aided methods have also been employed to solve nonlinear HVAC systems behavior, especially when the performance of the system is vulnerable to outside disturbance. Another recent work described explainable AI used on refrigeration systems to assist in the enhancement of efficiency and analysis states the increased influence of AI-based models in boosting energy performance and interpretability in cooling purposes [17]. Moreover, ANN-based models are created to monitor and predict COP in a vapor-compression system which proves that machine learning can reliably describe the performance behavior under the real working conditions and aid in adaptive optimization [18]. In addition to journals, the reinforcement learning-based control of vapor-compression refrigeration cycles has also been studied in conference research and it has been shown that intelligent learning-based controllers can operate near-optimally in simulated conditions [19]. Equally, there are still other HVAC-energy conferences (e.g., ASHRAE) that still publish applied literature concerning sustainable cooling, heat pump operation, and HVAC adaptation strategies in adverse weather conditions, which confirms the significance of advanced control strategies to thermal systems [20].

3. System Model (Baghdad, July–August 2024) And Control Variables

3.1 Ambient data source and time base (NASA POWER)

The simulations will be operated under hourly ambient conditions of Baghdad in July 1-August 31, 2024. The ambient dry-bulb temperature time series $T_{amb}(t)$ is obtained from the NASA POWER Hourly API, which provides analysis-ready hourly meteorological data suitable for direct use in simulation workflows [21]. In this work, the primary weather input is the 2-m air temperature (POWER parameter commonly provided for near-surface conditions), retrieved using the POWER parameter definitions and naming conventions described in the POWER parameter documentation [22]. The model time step is $\Delta t = 1$ hour, and each hourly sample is treated as a quasi-steady operating condition of the outdoor unit. Where, t is the time index (hour), $T_{amb}(t)$ [°C] is the outdoor ambient dry-bulb temperature at hour t(NASA POWER) [21], [22] and Δt [h]is the simulation time step (1 hour).

3.2 Split air-conditioning system description

A single-stage vapor-compression split air-conditioning system is considered. The indoor unit (evaporator + blower) is assumed to satisfy a required cooling demand, while the outdoor unit (condenser + fan + compressor) is the primary focus under high ambient temperature. The refrigeration cycle is represented using four main thermodynamic state points: (1) compressor inlet, (2) compressor outlet, (3) condenser outlet, and (4) expansion device outlet. This state-point structure and the associated energy balances follow standard vapor-compression cycle analysis references [23], [24]. Here five State points and enthalpies were defined:

- h_1[kJ/kg]: refrigerant enthalpy at compressor inlet
- h_2 [kJ/kg]: refrigerant enthalpy at compressor outlet
- h_3 [kJ/kg]: refrigerant enthalpy at condenser outlet
- h_4 [kJ/kg]: refrigerant enthalpy at expansion device outlet
- $\dot{m}_r$ [kg/s]: refrigerant mass flow rate

3.3 Refrigeration-cycle energy equations (cooling capacity, compressor power, COP)

At each hour, the cooling capacity $Q_e(t)$ and compressor power $W_{comp}(t)$ are computed from the refrigerant enthalpy differences using the standard steady-state relations [23], [24]:

$$Q_e(t) = \dot{m}_r(t)(h_1(t) - h_4(t)) \tag{1}$$

$$W_{comp}(t) = \dot{m}_r(t)(h_2(t) - h_1(t)) \tag{2}$$

The coefficient of performance is then:

$$COP(t) = \frac{Q_e(t)}{W_{comp}(t)} \tag{3}$$

Where,

- Qe [kW]: evaporator cooling capacity
- Wcom [kW]: compressor electrical/mechanical power (modeled via enthalpy rise)
- COP[–]: coefficient of performance
  These relations are widely used for vapor-compression cycle evaluation and are consistent with standard refrigeration thermodynamics formulations [23], [24].

3.4 Condenser heat-rejection model (UA–LMTD form with fan-speed dependence)

The outdoor condenser heat rejection is modeled using the overall heat transfer conductance concept UAUAUA, where the heat transfer rate is expressed using the log-mean temperature difference (LMTD) method [25]:

$$Q_c(t) = UA_{cond}(t)\Delta T_{lm}(t) \tag{4}$$

where $Q_c(t)$ [kW] is the condenser heat rejection rate and UA_{cond} [kW/K] is the effective overall conductance at hour t. The LMTD is:

$$\Delta T_{lm}(t) = \frac{(\Delta T_1(t) - \Delta T_2(t)}{\ln(\frac{\Delta T_1(t)}{\Delta T_2(t)})} \tag{5}$$

with $\Delta T_1(t)$ and $\Delta T_2(t)$ defined from the hot-side (condensing refrigerant temperature) and cold-side (ambient air) terminal temperature differences appropriate to the condenser configuration [25]. To represent the impact of condenser fan speed on air-side heat transfer, the condenser conductance is modeled as a speed-scaled relation:

$$UA_{cond}(t) = UA_0(t)(\frac{N_f(t)}{N_{rated}})^m \tag{5}$$

Where,

- Q_c [kW]: condenser heat rejection rate
- UA_{cond} [kW/K]: condenser overall conductance at time t.
- UA_0 [kW/K]: conductance at rated fan speed
- N_f [rpm or pu]: condenser fan speed (control variable)
- N_{rated} [rpm or pu]: rated fan speed
- m [–]: airflow-to-UA sensitivity exponent (chosen and later tested by sensitivity analysis)

The UA–LMTD framework is a standard heat-exchanger modeling approach used to link thermal performance to driving temperature difference and thermal resistances [25]. The above scaling captures the practical fact that increasing airflow (via fan speed) increases the external convection coefficient and thus the effective UA

3.5 Fan power model (affinity laws)

The condenser fan electrical power is modeled using fan affinity laws, which relate airflow, pressure, and power to rotational speed for geometrically similar operation [26], [27]. Fan power is approximated as:

$$W_{fan}(t) = W_{fan,rated}\left(\frac{N_f(t)}{N_{rated}}\right)^3 \tag{6}$$

Where,

- W_{fan} [kW]: condenser fan power
- $W_{fan,rated}$ [kW]: fan power at rated speed
- N_f [rpm or pu]: fan speed at time t.

This cubic relationship is a standard and widely used approximation for variable-speed fan energy modeling and is supported by fan-law references used in HVAC design and energy analysis [26], [27].

3.6 Compressor loading as a control variable

To represent compressor modulation (inverter-driven or equivalent capacity control), a compressor loading factor $u_c(t)$ is introduced as a normalized control input:

$$u_c(t) \in [u_{c,min}, u_{c,max}] \tag{7}$$

The loading factor adjusts the refrigerant mass flow rate:

$$\dot{m}_r(t) = \dot{m}_{rated} u_c(t) \tag{8}$$

Where,

- u_c [–]: compressor loading factor (control variable)
- $u_{c,min}, u_{c,max}$ [–]: minimum/maximum loading constraints
- m_{rated} [kg/s]: rated refrigerant mass flow rate

This representation is practical for simulation because it allows the study of capacity and power trends while keeping the thermodynamic structure of the vapor-compression cycle intact [23], [24].

3.7 Rated-condition anchoring and calibration (practical consistency)

To keep the model realistic, the rated parameters $\{UA_0, m_{rated}, W_{fan,rated}\}$ are calibrated so the system matches a typical split-unit rating point. The standard rating test conditions used with unitary air conditioning (commonly used as a reference when split systems and residential equipment are being benchmarked) are 80 o C (26.7 C) dry-bulb and 67 o C (19.4 C) wet-bulb of indoor air entering, and 95 o C (35 C) dry-bulb of outdoor air entering, under cooling standard rating conditions [28]. The rating methodology is widely applied in performance reporting and offers a common ground of model anchoring [28], [29]. After calibration at the rated condition, the model is driven by the hourly Baghdad ambient temperature $T_{amb}(t)$ to quantify degradation and improvement under extreme heat.

3.8 Simulation outputs and evaluation metrics

For each hour t, the model outputs:

$COP(t)$,$Q_e(t)$,$W_{comp}(t)$,$W_{fan}(t)$, and condenser heat rejection $Q_c(t)$.
The total electrical power is:

$$W_{tot}(t) = W_{comp}(t) + W_{fan}(t) \tag{9}$$

Monthly energy consumption over the simulation horizon T hours is:

$$E = \sum_{t=1}^{T} W_{tot}(t)\Delta t \tag{10}$$

where E is in kWh if W_{tot} is in kW and Δt is in hours.

4. AI-Assisted Supervisory Optimization Framework

4.1 Role of The AI Supervisor

Artificial intelligence will be utilized in this research as a supervisory optimization layer, which will run on top of the traditional thermodynamic model of the split air-conditioning system. The AI module does not substitute the physical laws of the vapor-compression cycle; it helps the mechanical system; it is adaptive, as it chooses the most suitable operating conditions of the outdoor unit in different ambient temperature conditions. In particular, the AI supervisor sets the appropriate values of condenser fan speed and compressor loading, depending on the real-time ambient conditions and system response, but the equations of the refrigeration cycle themselves are not changed. This hierarchical model shares concepts of supervisory control widely accepted in HVAC systems, in which intelligence based on the data assists but does not dictate the physical system behavior [30], [31].

4.2 Control Variables, Inputs, and Constraints

The AI supervisor acts on two primary **control variables** associated with the outdoor unit:

- Condenser fan speed $N_f(t)$
- Compressor loading factor $u_c(t)$

The input variables to the AI model include the ambient temperature $T_{amb}(t)$, condenser operating temperature $T_{cond}(t)$, and the current system performance indicators obtained from the mechanical model. Based on these inputs, the AI determines control actions subject to practical operational constraints:

$$N_{f,min} \leq N_f(t) \leq N_{f,max}$$

$$u_{c,min} \leq u_c(t) \leq u_{c,max}$$

These limits are the physical constraints of the fan motor and compressor drive, which promote harmless and realistic functioning. This constraint-based supervisory optimization has proven successful in the case of HVAC systems that control themselves in the conditions of nonlinear and disturbance-driven variables [31], [32].

4.3 Optimization Objective Function

The supervisory optimization problem is developed to improve the mechanical operation and the energy use during high ambient temperature operation. The main aim is to reduce the overall electrical power of the outdoor unit without compromising on satisfactory performance of cooling:

$$\min_{N_f(t),u_c(t)} J(t) \tag{10}$$

where the objective function $J(t)$ is defined as:

$$J(t) = W_{comp}(t) + W_{fan}(t) \tag{11}$$

subject to the cooling capacity constraint:

$$Q_e(t) \geq Q_{req}$$

and the operational constraints defined in Section 4.2. This formulation directly targets the main sources of performance degradation at high ambient temperatures—namely increased compressor power and reduced condenser effectiveness—while preserving the required cooling output. Similar energy-oriented objective functions have been widely adopted in AI-assisted HVAC optimization studies to balance efficiency and system stability [33], [34].

4.4 AI Model Implementation and Decision Logic

The AI supervisor is applied with a data-driven model that is able to reflect the nonlinear correlation that exists amongst the ambient circumstances, the control variables and the performance of the system. At every hourly time, the AI compares competitor control actions (N_f, u_c) and picks the combination that minimizes the objective function and meets all of the constraints. The process of this decision time is repeated with every hour with the revised ambient temperature data of NASA POWER.

Notably, the AI is a quasi-steady supervisory algorithm, i.e. the decisions of the control are not made continuously but at discrete time points. This methodology is also aligned with viable HVAC control architectures and minimizes redundant actuator switching and allows flexibilities to extreme temperature changes [31], [35]. Since the AI is implemented in the context of a physically consistent thermodynamic system, the suggested approach will make optimization decisions interpretable and mechanically meaningful.

5. Simulation Methodology

The offered system model and AI-assisted supervisory optimization framework are realized and tested with the help of MATLAB as the main simulation environment, as it has a great inclusion of numerical calculation, control development, and data-driven modelling. The temperature data of Baghdad at hourly recordings in JulyAugust 2024 is the data imported into the NASA POWER Hourly API and applied as external driving inputs into the simulation. Every hourly data is analysed as a quasi-steady operating condition of the split air-conditioning system. The Vapor-compression cycle thermodynamic model, condenser heat-rejection model, compressor loading logic, and fan power model represented in Sections 3 and 4 are simulated hour by hour. The key system parameters, including rated cooling capacity, rated compressor power, overall heat transfer coefficient of the condenser at rated conditions, rated power of the fan, and operation limits of fan speed and compressor loading, are selected to be that of a typical residential split air-conditioning unit and they are adjusted at standard conditions of rating before the simulations at the hot climate. Two simulation scenarios are taken: a control with traditional fixed parametrical controls and a case with AI-assisted control where the supervisory optimizer decides the compressor loading and condenser fan speed. Mechanical and energy related parameters are used to gauge system performance, such as coefficient of performance, compressor power consumption, fan power consumption, condenser operating temperature and total electrical energy consumed by the system during the period of the simulation.

In order to assess the efficiency of the proposed AI-assisted supervisory optimization when operating under the conditions of extreme hot climate, a set of simulations was performed based on the real hourly ambient temperature data on Baghdad in the months of July and August 2024, which were located in the NASA POWER data base. The findings are expressed in the form of five figures that are used to describe the severity of climate, trends of system performance, the behavior of energy consumption, and adaptive control of the AI supervisor. The figures are in a logical order beginning with the environmental conditions up to the system-level performance and control behavior.

Figure 1 shows the hourly fluctuation of ambient air temperature in Baghdad in the best months of summer July and August 2024. The data indicate a strong diurnal nature whereby daytime temperatures often go beyond 45 0 C and peak at around 50 51 C whereas night temperatures do not drop below 30 0 C most of the time. Such extreme and prolonged high ambient conditions put a cumulative constraint in condenser heat rejection in air-conditioning outdoor system, which in turn elevate condensing temperature, compressor power consumption, and system efficiency. This temperature characteristics indicates clearly the operation problems of air-conditioning systems in hot climates like Iraq and it is a good reason to explore adaptive control methods so as to prevent the degradation of performance in such conditions.

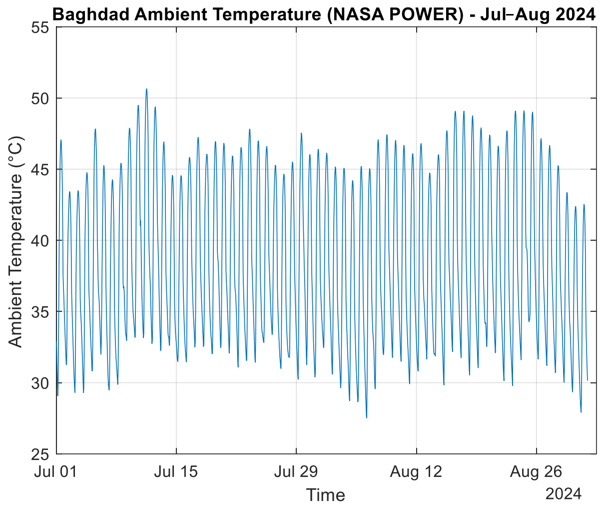

Figure 1. Hourly ambient temperature profile for Baghdad during July–August 2024 obtained from the NASA POWER database.

Figure 2 comparatively presents the temporal variation of the air-conditioning system coefficient of performance with the conventional baseline control and the proposed AI supervisory strategy. The two cases demonstrate significant day-to-day variables that are caused by the diurnal ambient temperature cycle, but the AI-based control will always have higher values of COP in the time when the ambient temperature outdoors is high. That performance improvement is also most evident during peak daytime periods when the rejection of condenser heat is the most limiting performance factor. The behavior is an indication that adaptive coordination of the speed of the condenser fan and the compressor loading contributes to reducing the degradation in efficiency in conditions of extreme thermal stress, resulting in system level performance without any changes in the basic refrigeration cycle.

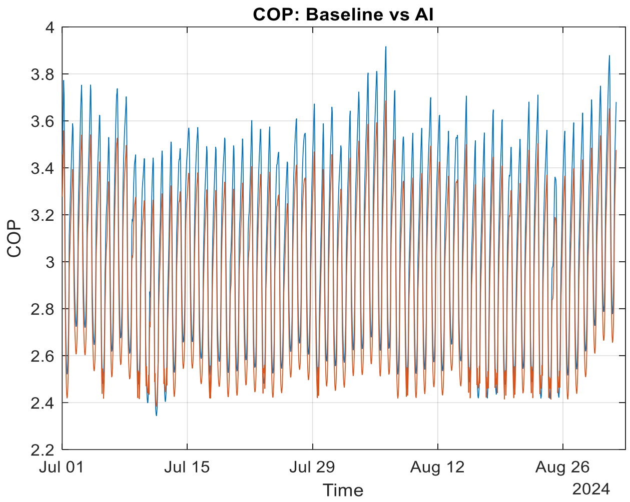

Figure 2. Coefficient of performance (COP) variation over time for the baseline and AI-assisted control strategies during July–August 2024.

The time-domain comparison of total electrical power consumption of the AI-assisted control strategy and the baseline control strategy is shown in Figure 3. The findings indicate that the AI-supported system can decrease the peak power demand consistently at the times of high ambient temperature and still provide the same power levels at lower temperatures. This action shows that the supervisory control proposed is mainly focused on operating conditions in which the heat rejection of the condenser is constrained, thus decreasing the compressor power demands. A decrease in peak power directly leads to the overall energy savings over the period of two months and demonstrates the possibility of the suggested method to reduce stress on electrical grid under extreme summer conditions.

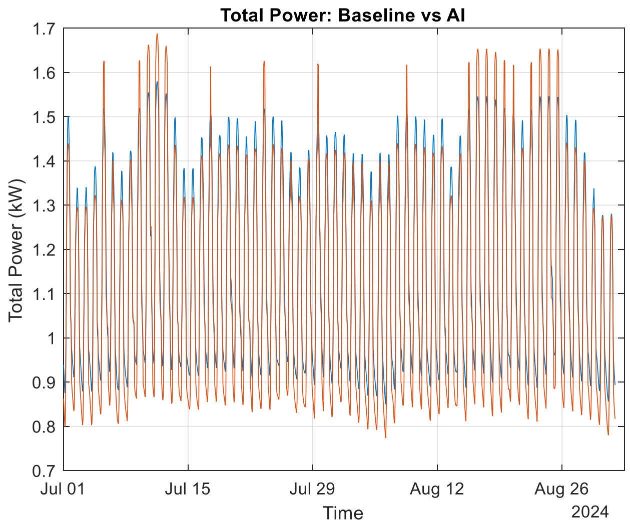

Figure 3. Total electrical power consumption of the air-conditioning outdoor unit under baseline and AI-assisted control during July–August 2024.

The dependency of both control strategies on ambient temperature on the air-conditioning system coefficient of performance is shown in figure 4. Thus, COP, expectedly, decreases with a rise in the outdoor temperature, as condenser heat-rejection capacity is reduced, compressor pressure ratio is higher. The AI-assisted control has improved CO2 at high temperatures, and the magnitude of this improvement is stronger in the high temperatures that are above around 42-45 C. This pattern attests the fact that the presented supervisory optimization is especially efficient when the thermal conditions are at their extremes with a synchronized regulation of the condenser fan speed and compressor loading aiding in the alleviation of the efficiency loss.

Figure 5 shows the control values produced by the AI supervisory optimizer with regard to the condenser fan speed and compressor loading during the course of the simulation. The findings show that the AI is mainly adding more condenser fan speed at the times when ambient temperature is high whereas compressor loading is changed in a more limited and conservative range. Such a behavior is indicative of a physically interpretable approach where better condenser heat rejection is made more important to prevent the excessive compressor loading in extreme thermal conditions. The fact that the suggested solution does not imply any aggressive or turbulent switching also proves that the given solution is compatible with the real-world hardware related to air-conditioning, and it does not exert unnecessary mechanical loads on the elements of the system.

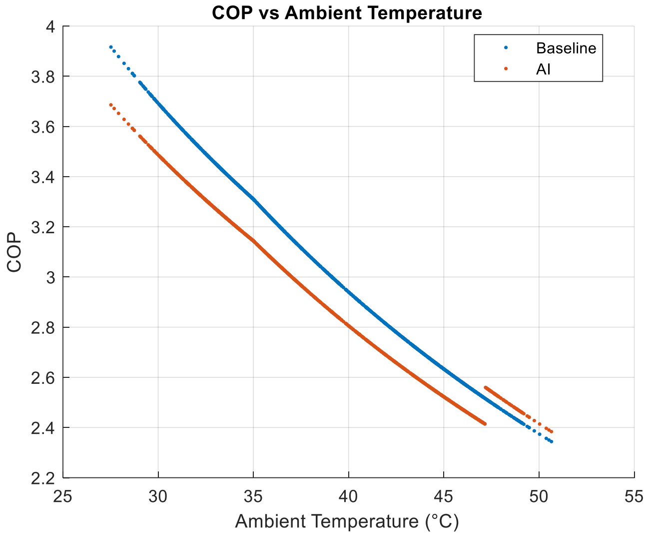

Figure 4. Relationship between the coefficient of performance (COP) and ambient temperature for baseline and AI-assisted control strategies.

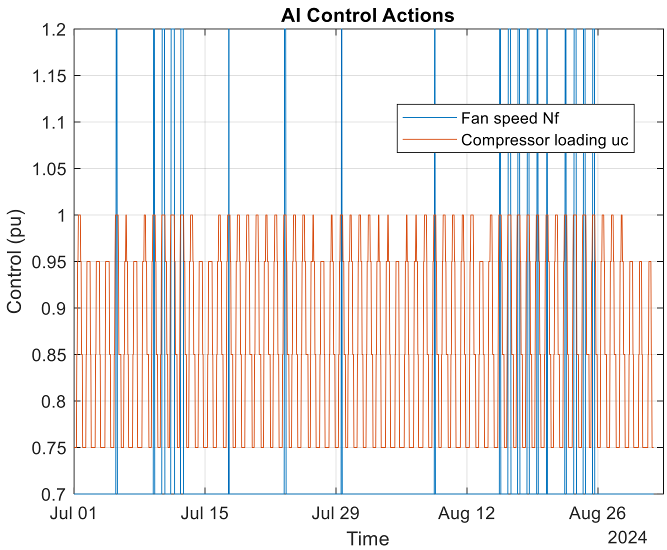

Figure 5. AI-assisted control actions for condenser fan speed and compressor loading during July–August 2024.

5.1 AI-Assisted Actuation and Physical Performance Improvement Mechanism

As shown in Figure 6, the suggested AI-aided framework is an enabled supervisory control layer, which integrates existing actuation devices of the air-conditioning external unit. The thermodynamic model then processes real-time ambient temperature, system operating variables and feeds them into the AI optimizer which then decides the appropriate setpoints of the condenser fan speed and compressor loading within established boundaries of operation. Such setpoints are then executed by using typical inverter-based actuators that are typically found in the contemporary split air-conditioning systems. The physical performance gain comes mainly through the increased condenser heat rejection which is made possible through adaptive airflow control that reduces operating temperature of the condenser and compressor pressure ratio when ambient conditions are high. Simultaneously, synchronized loading of compressors prevents inefficient running at too high levels of discharge pressures. This actuation strategy of supervisory enhances system efficiency, as well as minimize consumption of electrical power without the need to change the basic refrigeration cycle, which makes the suggested strategy viable and applicable to use in hot climate environments.

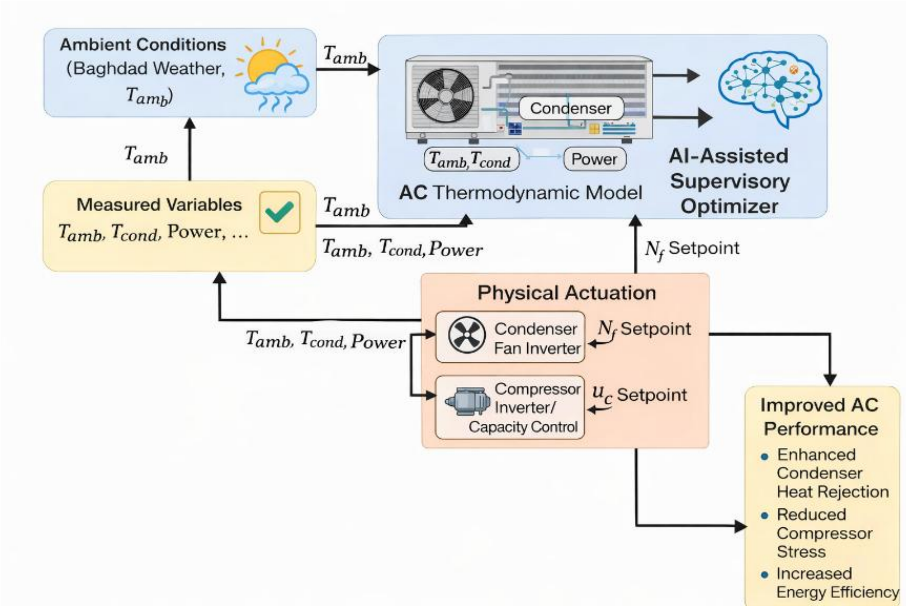

Figure 6. Block diagram of the AI-assisted supervisory control framework showing the interaction between environmental inputs, system model, AI optimizer, and physical actuation of the air-conditioning outdoor unit.

6. Conclusions and Future Work

This work presented an AI-assisted supervisory optimization framework for improving the performance of a split air-conditioning outdoor unit operating under extreme hot-climate conditions representative of Baghdad during July–August 2024. Using real hourly ambient temperature data from the NASA POWER database, the proposed approach coordinated condenser fan speed and compressor loading without modifying the refrigeration cycle. Simulation results showed an overall energy reduction of approximately 3.2% compared to conventional control, along with improved coefficient of performance and reduced peak power demand during high ambient temperature periods. The results indicate that performance degradation in hot climates is primarily driven by condenser heat-rejection limitations, and that adaptive coordination of existing actuators can effectively mitigate this issue in a physically interpretable and practical manner. Future work will focus on experimental validation, incorporation of additional climatic variables, and extension of the supervisory framework toward predictive and multi-objective optimization to further enhance energy efficiency and system reliability in hot-region applications.

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