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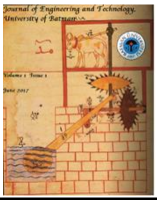

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Numerical Model for Thermal Performance Analysis of Panel Radiator

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ABSTRACT

In this study, a numerical model was developed to analyze the thermal behavior of a panel type (PKP) aluminum radiator used for space heating. The developed model was applied to a slice of the radiator and, convection and radiation effects were included in the calculations. Model accuracy tests were performed in the test room located in the Thermal Sciences Laboratory of the Mechanical Engineering Department of the Faculty of Engineering at Gazi University, using the experimental results performed according to the TS EN 442 standard on the market equivalent of the analyzed radiator. The test room was equipped according to the ANSI/ASHRAE-138 standard and made suitable with the EN 442 radiator test. The numerical analysis results showed that; 600-800-1100-1400 W thermal power can be obtained for 30-40-50-60^{o}C temperature differences using the radiator under study and the heat transfer coefficient of the radiator is an average of 6.35 W/m^{2}K.

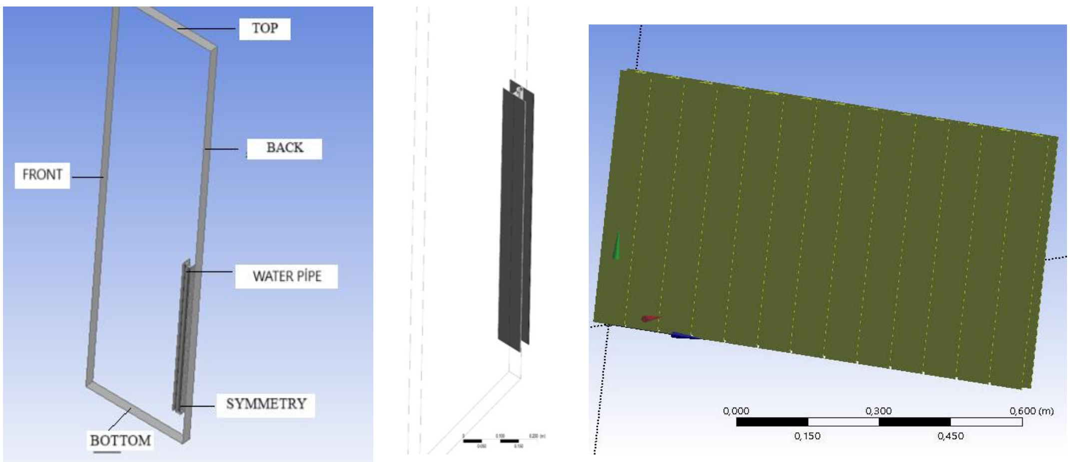
1. Introduction

With approximately 45% of the world's total energy consumption, buildings are one of the largest energy consumers [1]. Building heating contributes significantly to this proportion. Therefore, the demand for heating systems with higher efficiency and thermal output is on the increase day by day. One of the most widely used heating devices for the heating of buildings is the panel radiator with convection fins (convector) [2, 3]. Therefore, it is important to increase the thermal output of panel radiators. The thermal performance of panel radiators is affected by the internal fin designs, water channels, and ventilation holes and grilles. In this study, the panel radiator slice is examined and the thermal performance of the radiator is determined. The design of the convectors that are used in the panel radiators has a significant impact on the determination of the total thermal output of the radiator. Therefore, in order to achieve the highest possible thermal output of panel radiators, the geometry and dimensions of the convectors play an important role. For the purpose of getting higher thermal efficiency, it is focused on the internal design of the panel. Although the majority of the heat transfer from panel radiators occurs by natural convection, the contribution of radiation was observed to be around 26% for an inlet/outlet temperature of 75/65 °C [4]. The hot water circulating in the pipes transfers its energy to the ambient air by convection and radiation through the panels and convectors. The temperature difference between the radiator surfaces and the ambient air is the main factor that causes heat transfer. In order to increase the convective heat transfer, most panel radiators are equipped with convective fins (convectors) [5]. Recent studies have focused on enhancing the thermal efficiency of domestic convectors. Embaye et al. [6] and Calisir et al. [7] examined the impact of pulsating flow regimes on energy consumption in Type 10 and Type 11 convectors. Their findings suggest that constant flow rates fail to optimize heating performance, whereas intermittent flow conditions significantly improve efficiency. Computational Fluid Dynamics (CFD) simulations were employed to analyze localized flow dynamics within the convector systems. Marchesi et al. [8] experimentally compared the thermal behavior of traditional cast iron and modern aluminum convectors under varying hydraulic configurations, flow rates, and mounting positions. Their results demonstrated that aluminum convectors exhibit superior thermal efficiency. Dzierzgowski [9] identified limitations in the EN-442 standard [10], revealing a 22.3% underestimation of thermal output for cast iron convectors under low-flow conditions through tests involving multiple convector types and operational parameters. Calisir et al. [11] analyzed geometric parameters (e.g., panel height, wall thickness, trapezoidal geometry) and concluded that increasing material thickness and panel height enhances heat transfer, albeit at elevated costs. Gritzki et al. [12] questioned the reliability of EN-442 for Type 22 convectors, particularly at reduced flow rates, and explored how inlet-outlet configurations and flow direction adjustments influence heating performance. Beck et al. [13] proposed a novel double-panel convector design incorporating radiative plates, which reduced manufacturing complexity and dust accumulation compared to traditional finned designs but introduced trade-offs in thermal output. Despite these advancements, a systematic investigation linking inlet water temperature, flow rate variations, and localized thermal characteristics in domestic convectors remains absent. This study addresses this gap through experimental analysis of thermal dynamics and the development of a predictive model for average surface temperature.

2. Methodology

2.1 Model Definition

For a radiator with a height of 600 mm, a length of 1000 mm and an inner diameter of 13.3 mm water pipe, the thermal performance of an aluminum panel slice is simulated using ANSYS. The slice width of the radiator is 8 cm and the thickness is 4 cm. A domain size of 460x40x1600 is used in the analysis. The panel has fins, water pipe and air channels in the rear section, and the geometry and boundary conditions of these components are given in Table-3.



(a) Boundary conditions of model (b) A slice of aluminum radiator model (c) Aluminum radiator model

Figure 1. Numerical model solution domain and boundaries for the radiator slice: (a) Boundary conditions of model (b) A slice of aluminum radiator model (c) Aluminum radiator model

2.2 Governing Equations

In this study, the continuity equation, the momentum equation and the energy conservation equation for the air inside the radiator slice and the radiation equation between the air and the radiator are solved together. The continuity equation is reduced to the following form by the assumption that the Boussinesq equation is incompressible,

$$\vec{\nabla} \cdot \vec{v} = 0 \tag{1}$$

The symbol $\vec{v}$ in Equation (1) represents the velocity of the air.
The momentum equation takes the following form when the effect of buoyancy and viscous forces are taken into account,

$$\vec{\nabla} \cdot (\vec{v}\,\vec{v}) = -\frac{\vec{\nabla} P}{\rho} + \frac{1}{\rho}\vec{\nabla} \cdot \left(\mu\left(\vec{\nabla}\vec{v} + \left(\vec{\nabla}\vec{v}\right)^T\right)\right) - \vec{g}\beta \quad (T - 293.15) \tag{2}$$

In this equation, P represents the air pressure, ρ the density of air, μ the viscosity of air and it is assumed to vary with temperature.
The energy equation is reduced to the following form under the influence of advective and conduction terms,

$$\vec{\nabla} \cdot (\vec{v}\,h) = \frac{1}{\rho}\vec{\nabla} \cdot \left(k\vec{\nabla} T\right) \tag{3}$$

The term h in equation 3 is the enthalpy of the air and k is the thermal conductivity of the air.

The discrete ordinate model given in Equation 4 was used to solve the radiative heat transfer between the radiator surface and the surrounding environment simultaneously with the conservation equations.

$$\nabla \cdot (I_\lambda(\vec{r},\vec{s})\vec{s}) + (a_\lambda + \sigma_s)I_\lambda(\vec{r},\vec{s}) = a_\lambda I_{b\lambda} + \frac{\sigma_s}{4\pi}\int_0^{4\pi} I_\lambda(\vec{r},\vec{s}\,')\Phi(\vec{s}\cdot\vec{s}\,')d\Omega' \tag{4}$$

In Eq. 4, λ is the wavelength, a_λ is the spectral absorption coefficient and I_λ is the radiation intensity.

The turbulence model used was the SST k-ϖ model. Details of the SST k-ϖ model are given in Menter's study [14].

2.3 Material Properties

The characteristics of the aluminium radiator materials used in the market are given in Table-2.

Table 1. Properties of aluminium material used in the analyses

Property	Value	Unit
Density	2719	kg/m³
Specific heat (Cp)	871	J/(kg·K)
Thermal Conductivity	202.4	W/(m·K)

The thermophysical properties of air are given in Table-3. The Sutherland model[15] used for dynamic viscosity in the material properties of air is given in Eq. (5).

$$\mu = 1{,}716 \times 10^{-5}\left(\frac{T}{273{,}11}\right)^{\frac{3}{2}}\frac{273.11 + 110.56}{T + 110.56} \quad \left[\frac{kg}{m\,s}\right] \tag{5}$$

Table 2. Properties of air used in the analyses

Property	Value	Unit
Density	1.11267	kg/m³

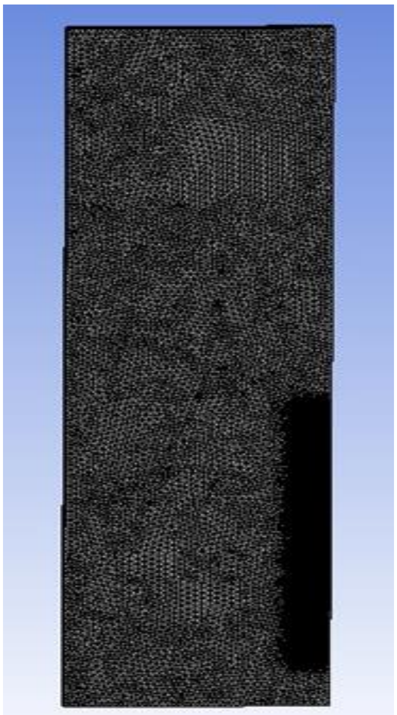
Specific heat (C_p)	Segmented polynomial	J/(kg·K)
Thermal Conductivity	Polynomial	W/(m·K)
Dynamic Viscosity	Sutherland model	kg/(m·s)
Absorption Coefficient	0.01	1/m
Scattering Coefficient	1E-05	1/m
Scattering Phase Function	Isotropic	-
Thermal expansion coefficient	0.00341122	1/K
Refractive Index	1.0003	-

The thermal conductivity polynomial is formed according to the working range and is given in Eq. (6).

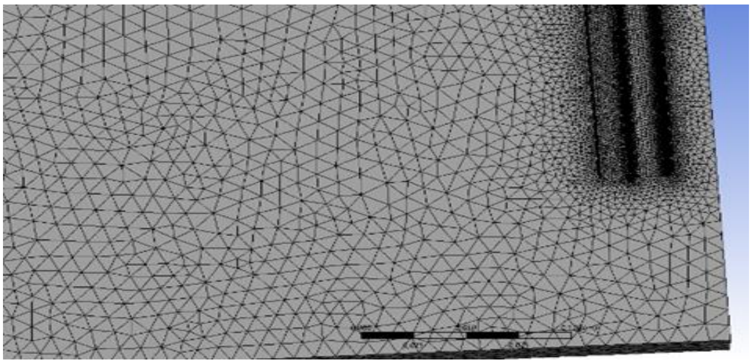
$$k = 1.1144132 \times 10^{-3} + 9{,}324767 \times 10^{-5} T - 3{,}63004 \times 10^{-8} T^2 \left[\frac{W}{mK}\right] \tag{6}$$

2.4 Mesh Structure

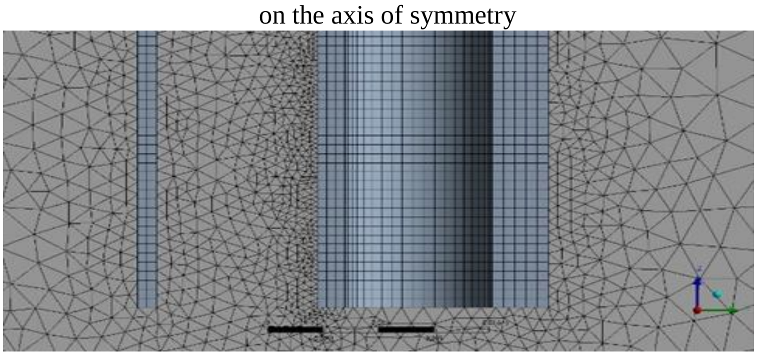
An important parameter that directly affects the accuracy of the model and the reliability of the solution is the mesh structure created for the finite element analysis of the panel slice. In this study, an attempt was made to keep the skewness, number of elements and orthogonal quality values, which indicates the quality of the mesh created to solve the numerical model, at minimum values to ensure convergence of the results and independence from the mesh structure. Accordingly, the number of mesh elements was set to 2.965.115, the maximum value of skewness was set to 0.978 and the minimum value of orthogonal quality was set to 0.1 and the mesh structure was formed as shown in Figure-2.



a) View from the mesh structure on the symmetry axis in the entire solution domain



(b) View from the mesh structure around the panel-water pipe on the axis of symmetry



(c) Symmetry axis view of the mesh structure in and around the panel-water pipe

Figure 2. Solution region used in the numerical model for the radiator slice: (a) View of the mesh structure in the symmetry axis in the entire solution region (b) around the water pipe-panel (c) in and around the panel-water pipe

2.5 Boundary Conditions

The boundary conditions used in the analysis are given in Table-3. The analyses were performed in 4 different ways by applying variable temperature conditions in the water pipe. Constant temperatures were set for the water pipe and different temperature values were applied. Adiabatic conditions were provided on the bottom and back walls and a certain emission coefficient was used for radiation. On the front and top surface, the outlet pressure was defined as 1 atm and radiation conditions were taken into account. For the radiator walls, solid-fluid interface conditions were applied and the radiation emission coefficient was specified.

Table 3. Boundary conditions for numerical model solution region

No	Boundary	BC	Thermal BC		Radiation BC
1	Water pipe	Constant Temp.	A1	T=50ºC	N/A
			A2	T=60ºC	
			A3	T=70ºC	
			A4	T=80ºC	
2	Ground-back wall	Wall	Adiabatic		ε= 0,98
3	Front-Top	Pressure Outlet	P = 1 atm		ε =0,98
4	Radiator Walls	Wall	Solid-liquid interface		ε =0,95
5	Symmetry	-	-		-

3. Introduction of Test Chamber, Test Specimen and Experimental Setup

Capacity determination tests were performed according to TS EN 442-2 standard in test room designed according to ANSI/ASHRAE 138 standard, where air temperature and wall surface temperatures can be controlled, located in Gazi University Mechanical Engineering Department Heat Science Laboratory, shown in Figure-3,4,5.

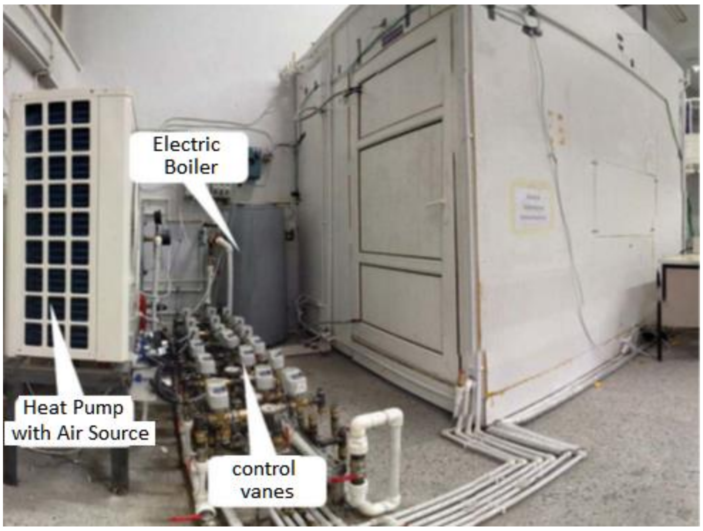


Figure 3. View of the test chamber and mechanical installation equipment

Test samples: MARKET ‘Type 21 PKP Aluminium Panel Radiator’
The front and top views of the tested radiator are presented below;

Figure 4. Aluminium 600*1000 (13 sections) Radiator - thermocouple locations

Figure 5. View of the radiator test measurement set-up

4. Experimental Method

The panel radiator to be tested is mounted in the middle of the wall in the test room at a height of 50 cm from the floor. The water inlet and outlet temperatures and the water flow rate of the panel radiator are measured. The panel radiator is supplied with hot water at 75^{o}C and the water flow rate is adjusted so that the radiator outlet temperature is 65^{o}C. The indoor temperature of the test room is measured from four different positions (5 cm from the ceiling, 5 cm from the floor, 75 cm and 150 cm) specified in the standard on a vertical rod placed in the centre of the room. The test room is conditioned by cooling from the walls other than the wall where the radiator is located, so that the room temperature is maintained at 20 ^{o}C. The average surface temperature of the radiator is calculated using data from three thermocouples placed on the infeed, mid-feed and outfeed surfaces.

Unlike the TS EN 442-2 standard, this test was carried out by feeding water heated by an electric heater in a chamber directly to the radiator by means of a circulating pump. The difference is in the method used to measure the water flow rate, in this test the water flow rate was measured using a calibrated flow meter. The accuracy of the flow meter is ±0.471 g/s. The method used to determine the thermal output, as specified in the standard, is to measure the water flow through the radiator and to measure the temperatures at the supply and return connections to determine the enthalpy difference.

5. Results

Figure 6 shows the results of the analyses carried out on a section of the radiator at (a) the front, (b) the side and (c) the back. The flow curve and velocity of the ambient air at room conditions are shown. The hottest region in a slice is at the center line. The lower end of the radiator has the lowest temperature. The temperature of the metal increases as it rises. Because the water pipe of the radiator is closer to the back surface, the back surface is hotter than the front surface. The air flow in the radiator is accelerated from bottom to top. As the temperature of the air entering the radiator and the region with the lowest boundary layer thickness is at the bottom, the highest heat transfer coefficient occurs at the bottom.

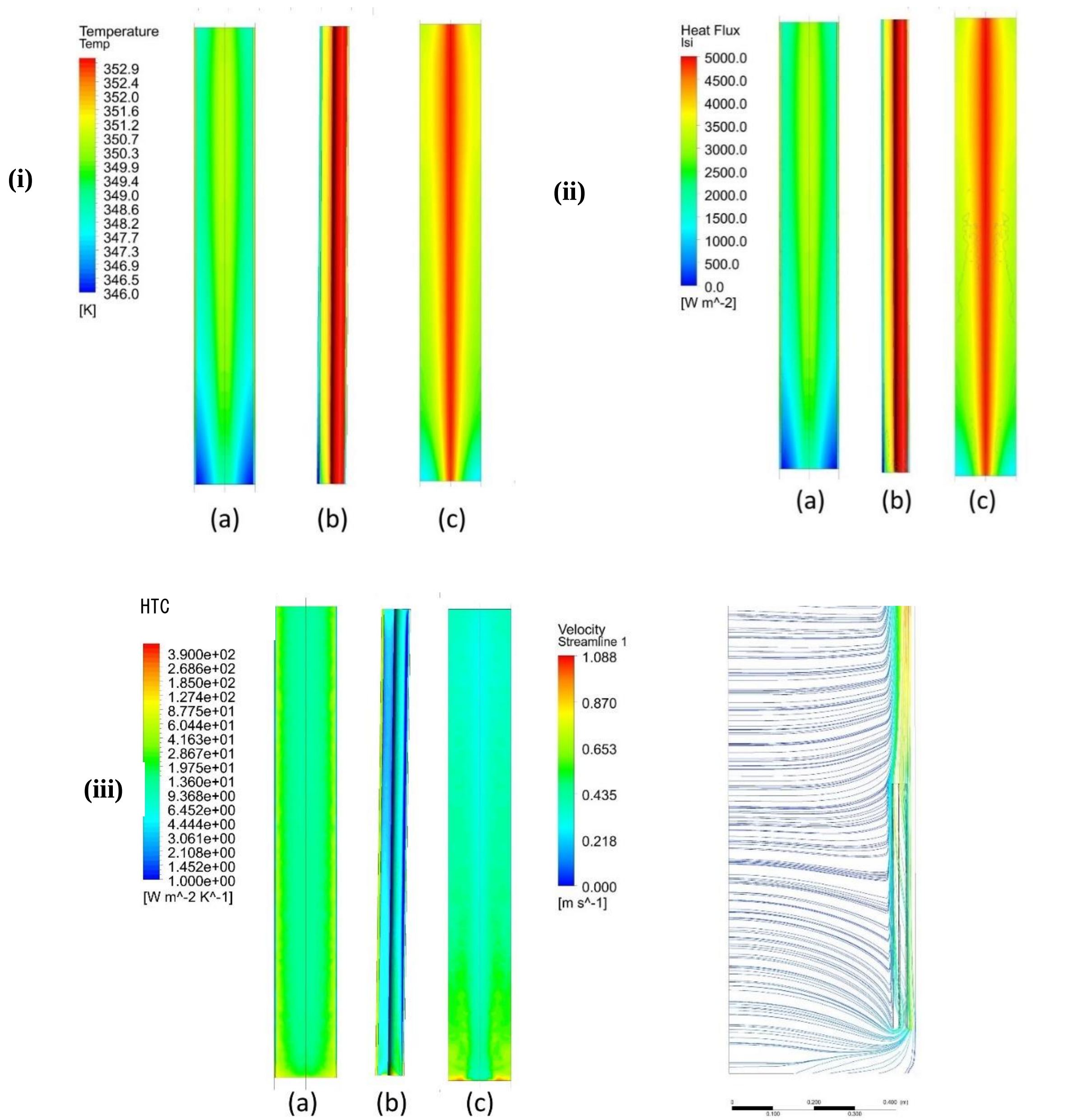


Figure 6. Radiator slice (i) temperature, (ii) heat flux, (iii) heat transfer coefficient (HTC) and air flow (velocity) distributions for $\Delta T = 60$ K

The radiator thermal power was calculated by taking the sum of the local heat flux obtained over the water pipe wall as a result of the analysis over the surface area,

$$Q = \int q'' \cdot d\vec{A} \tag{7}$$

and the average heat transfer coefficient was calculated using the following integral,

$$h_{avg} = \frac{1}{A}\int \frac{q'' \cdot d\vec{A}}{T - 293.15} \tag{8}$$

The analyzed radiator consists of 13 slices. Therefore, while calculating the radiator thermal power, the numerical result obtained for the slice was multiplied by the number of slices.

The radiator heat transfer coefficient is the same as the radiator slice heat transfer coefficient and is calculated by taking the integral of the local heat flux on the radiator panel surfaces divided by the local temperature difference (difference between local water temperature and ambient temperature) over the total surface as a result of the analysis.

The thermal power and heat transfer coefficients obtained as a result of numerical analysis are given in Table-4.

Table 4. Radiator power and average heat transfer coefficient obtained in the analysis

Temperature Difference, ΔT [°C]	Water Inlet Temperature, T_{in} [°C]	Water Outlet Temperature, T_{out} [°C]	Radiator Thermal Power, P [W]	Average Heat Transfer Coefficient, $\underline{HTC}$ [W/m^2 K]
30	55	45	538	5.63
40	65	55	781	6.15
50	75	65	1040	6.57
60	90	70	1335	7.05

6. Evaluation of The Results

Radiator thermal power values obtained as a result of computational fluid dynamics (CFD) analysis are presented in Figure-6. The market equivalent radiator of the analyzed radiator was tested in accordance with TS EN 442 standard in the test room installed in the Thermal Science Laboratory of Gazi University Faculty of Engineering, Department of Mechanical Engineering. The difference between the average temperature of the water in the radiator and the ambient temperature was 50°C. The radiator thermal power was measured as 1050 W and the heat transfer coefficient was calculated as 7.18 W/m2K. As a result of the numerical analysis, the radiator thermal power was calculated as 1040 W and the heat transfer coefficient was calculated as 6.57 W/m2K. As a result, it was determined that the numerical analysis model gave results compatible with the experiments and its accuracy was proved.

In Figure 7, the radiator thermal powers obtained from the numerical results according to the change of the difference between the average water temperature inside the radiator and the ambient temperature are shown as dots and the correlation curve is shown with a dashed curve. The formulation of the correlation curve obtained in Figure-7 is given by Equation 9.

$$Q = 7{,}881154\, L\, (\Delta T)^{\frac{5}{4}}\ [W] \tag{9}$$

In Eq. (9), ΔT represents the temperature difference [K] and L represents the radiator length [m].

The exponential value of the correlation proposed in the literature for natural convection [16] was found to be 5/4, the same as the value obtained in this study. In the light of these results, it was determined that the model developed for the numerical analysis of the radiator gives results compatible with both the literature and experiments and can be used in different types of radiator thermal power calculations and heat transfer coefficient calculations.

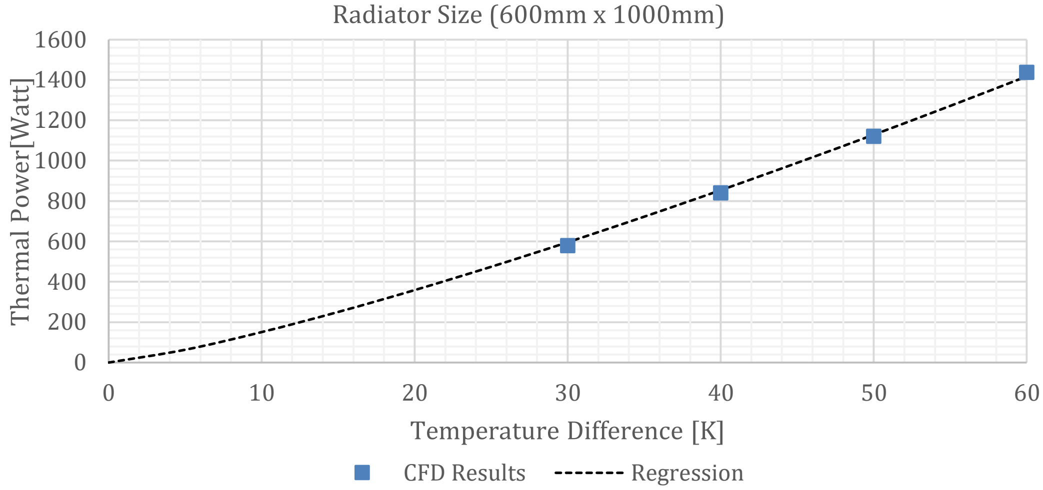


Figure 7. Radiator thermal powers according to temperature difference

Table 5. Radiator power and average heat transfer coefficient obtained in the analysis

Temperature Difference (ΔT)	Experimental thermal power (W)	Numerical Thermal Power (W)	Regression Estimation (W)	Error Rate (%) (Experimental vs. Numerical)
30 K (30°C)	484,0	538	479,6	+10,0
50 K (50°C)	980,4	1040	1048	+5,7
60 K (60°C)	1259,9	1335	1362	+5,7

For ΔT = 30°C, the experimental thermal power (484 W) is approximately 10% lower than the numerical result (538 W) in Table 5. This discrepancy may arise due to weak natural convection at low temperature differences and the model's inability to fully capture boundary layer effects. For ΔT = 50°C and 60°C, the error rate is 5.7%, indicating that the model produces closer predictions to experimental data at higher temperature differences. The regression curve in Equation 9 aligns almost perfectly with the numerical results but shows slight deviations compared to experimental data. This suggests that the regression is based on numerical data and does not fully account for practical limitations in experimental conditions, such as heat losses or measurement precision.

The experimental methodology was meticulously executed in accordance with the TS EN 442-2 standard, thereby ensuring optimal reliability and reproducibility. Tests were conducted in a controlled environment that was compliant with ANSI/ASHRAE-138. In this environment, the temperature of both the walls and the air were regulated with a high degree of precision, with the target temperature set at 20°C. Key parameters, including water flow rate (±0.471 g/s accuracy) and inlet/outlet temperatures (±0.1°C precision), were measured using calibrated instruments, as detailed in the provided test results table. For instance, at a temperature difference of 50°C, the measured thermal power (980.4 W) closely aligns with the numerical prediction (1040 W), with a mere 5.7% deviation, thereby underscoring the consistency of the experimental setup. Furthermore, corrections for barometric pressure effects were applied (e.g., Φ = 484.0 W at ΔT = 30°C), and repeated trials under identical conditions yielded minimal variability, as demonstrated in the tabulated data. The employment of multiple thermocouples for the calculation of surface temperatures, in conjunction with the adherence to the enthalpy-based calculation method stipulated in EN 442, serves to further substantiate the veracity of the results obtained. This meticulous approach aligns with established studies on radiator performance evaluation, thereby reinforcing the credibility of the experimental outcomes for both academic and industrial applications.

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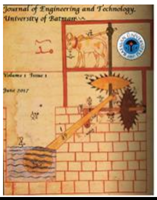

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Sensors in Microgrids and IoT Technologies

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ABSTRACT

This article examines the importance of sensors used in microgrids for energy management and their impact on system efficiency, reliability, and sustainability. The primary research question addresses the contribution of sensors to the effective management of microgrids and their critical roles in energy production, distribution, and consumption processes. The methodology focuses on the integration of various sensor types with smart energy management systems and the analysis of IoT-based solutions. The article analyzes the role of smart sensors, wireless sensor networks, and IoT-based sensor integrations in optimizing the performance of microgrids. The findings indicate that sensors help maintain the balance between energy production and consumption, reducing energy costs and enhancing system stability. It is particularly highlighted that sensors play a critical role in mitigating the variability of renewable energy sources. In conclusion, it is emphasized that sensor technologies will play a more central role in energy management processes in the future, enhancing energy efficiency and contributing to sustainable energy management. Accordingly, the development and integration of sensors will continue to lead innovation in the energy sector.

1. Introduction

Microgrids are becoming increasingly important in energy management and distribution, particularly with the integration of renewable energy sources. These systems aim to enhance energy efficiency, ensure reliability, and strengthen sustainability by bringing together small-scale energy production, storage, and consumption units. The successful management of microgrids is critical for balancing variable and intermittent renewable energy sources such as solar and wind. This balancing relies on the data provided by sensors integrated into smart energy management systems.

The objective of this study is to examine the contributions of sensor technologies to the optimization of energy systems in microgrids. Sensors play a critical role in maintaining the balance between energy production and consumption, enhancing system stability, and enabling the effective integration of renewable energy sources. In this context, the significance of the study lies in highlighting the role of sensors in reducing energy costs and fostering sustainable energy solutions. Looking ahead, advancements in sensor technologies are expected to play a pioneering role in making energy systems smarter and more efficient.

2. Basic Sensor Types

With the use of IoT-based sensors in microgrids, the necessity of managing multi-layered structures in harmony has emerged. The place and functioning of sensors in the microgrid infrastructure; IoT-based microgrid architecture (layered structure such as sensor layer, network layer, application layer), data flow diagram (from sensors to cloud, analysis layer) and sensor communication network topology are given in Figure 1 [1-4].

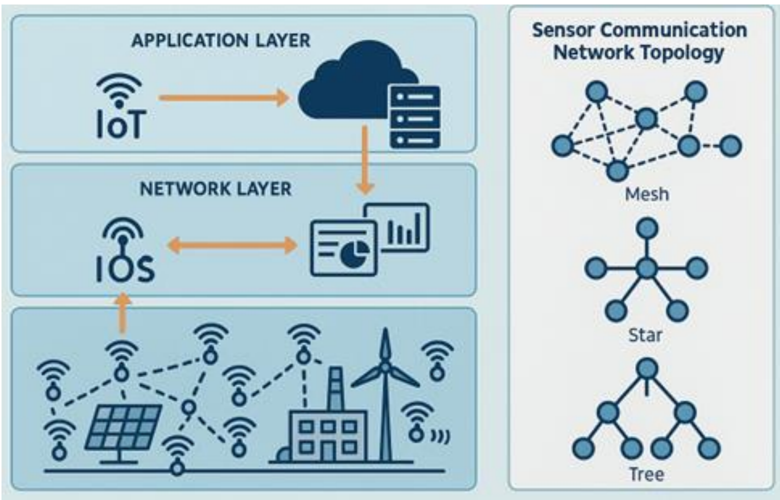

Figure 1. IoT based microgrid architecture

Many different types of sensors are used in microgrids depending on their intended use. General trends of the most commonly used sensor types in microgrids, based on literature reviews and industry reports, are given in Figure 2 [1-4].

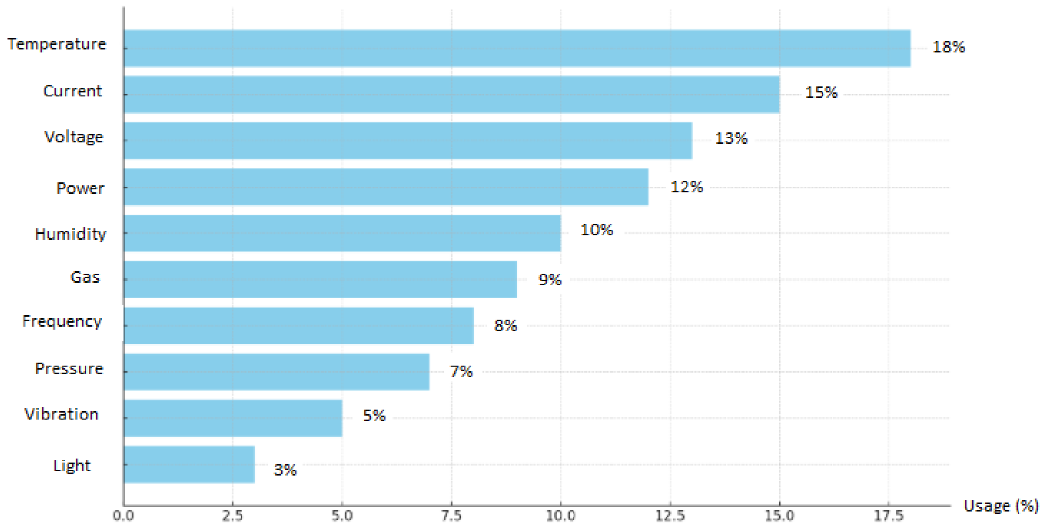

Figure 2. Distribution of sensors used in microgrids

2.1 Current sensor

Current sensors provide data to energy management systems in microgrids by monitoring the current drawn by devices and lines [5]. These sensors optimize energy flow, balance loads, and protect the system by detecting overcurrent conditions. They are employed in generators, solar panels, wind turbines, energy storage systems, and power converters to enhance efficiency and provide protection against overloads [6]. Additionally, current sensors monitor energy flow in distribution lines, detect imbalances, and trigger circuit breakers in hazardous situations, ensuring system safety. The types of current sensors used in microgrids are outlined below:

Hall Effect Current Sensor: These sensors measure current non-invasively by detecting magnetic fields [7]. They are commonly used in high-current applications. Accuracies up to 0.5%, measuring range up to ±1000 A. They are affected by temperature variations, magnetic saturation and offset deviations. In closed loop Hall sensors, error compensation methods can be applied in low current ranges [8].
Rogowski Coil: Particularly suitable for monitoring large current values, these sensors operate with a coil wrapped around the conductor carrying the current [9]. Sensitivity is in the range of 0.1-1.0% and is effective at high currents (kA levels). Good performance at high frequency currents, no saturation problem. Sensitivity depends on coil positioning and frequency content [10], [11].
Shunt Resistor: This method directly measures current by evaluating the voltage drop across a small resistor through which the current flows [12]. Their accuracy is up to 0.1% and they usually have a measurement range of 0-600 A. Temperature variations and interference can cause measurement errors. Cooling and calibration are important for low cost and high accuracy [13].
Current Transformer (CT): Designed for high-current measurement, these transformers reduce current to a lower level, making it safer and easier to monitor [14]. Measurement class according to IEC 61869 standard ranges from 0,1 to 1. Typical accuracy is between ±0,5% and ±1%. Sources of error can occur due to signal distortion and magnetic saturation [15], [16].

2.2 Voltage sensor

Mikro şebekelerde kullanılan gerilim sensörleri; elektrik sistemindeki gerilim seviyelerini izler ve bu Voltage sensors in microgrids monitor voltage levels within the electrical system, ensuring safe and efficient operation by maintaining stability [17]. They regulate voltage fluctuations during energy generation and distribution, trigger protection relays during overvoltage events, and safeguard equipment. These sensors monitor voltage levels in solar panels, wind turbines, generators, and batteries, ensuring energy quality and safety. Additionally, they are employed in inverters and converters for voltage regulation, enhancing system stability.
The types of voltage sensors used in microgrids are listed below:
Voltage Transformer (VT): These sensors step down high voltage levels to lower, measurable levels [18]. They are widely used in large energy generation facilities and distribution networks. According to the IEC 61869 standard, accuracy classes are 0.1%, 0.2%, 0.5% and 1%. Voltage transformers used in medium voltage applications generally operate with a ratio error of 0,5% to 1%. However, harmonic distortions can affect this accuracy [19].
Hall Effect Voltage Sensor: This type of sensor performs contactless voltage measurement through magnetic fields [20]. It can accurately measure both AC and DC voltages. Hall-effect voltage sensors measure voltage due to the influence of a magnetic field and typically offer an accuracy of 0,5-1.0%. However, temperature variations and electromagnetic interference can affect measurement accuracy. They offer the advantage of isolation and compactness.
Optical Voltage Sensor: These sensors utilize optical fibers for voltage measurement [21]. Suitable for high voltage applications. Especially used in critical applications as it is not affected by electromagnetic interference. Mechanical disturbances and temperature variations can affect its performance. At voltages above 100 V, it offers ±0,2% accuracy; for voltages of 200 V and above, the accuracy goes up to ±0,1% [22].
Capacitive Voltage Sensor: These sensors measure voltage by utilizing the capacitance between two points [23]. They are typically preferred in low-cost applications. Can be used over wide voltage ranges. It has high accuracy and low power consumption. Environmental conditions and temperature changes can affect its performance [24].

2.3 Power sensor

Power sensors in microgrids are crucial for monitoring and controlling power flow (consumption and generation) [25]. These sensors continuously monitor active and reactive power, performing both AC and DC measurements. Data from the sensors is transmitted to energy management systems (EMS), balancing power demand and generation. By detecting excessive power draw and imbalances, they trigger protection circuits to prevent equipment damage. They also detect harmonic distortions and fluctuations, ensuring the accurate conversion of power in inverters and converters.
The types of power sensors used in microgrids are listed below:

Current and Voltage-Based Power Sensor: These sensors combine current and voltage data to calculate instantaneous power values [26]. These sensors calculate power based on current and voltage measurements. Accuracy depends on the sensitivity of the current and voltage sensors used. Typically, ±0,5% accuracy can be achieved [27].

Hall Effect Power Sensor: These sensors perform contactless power measurements through magnetic fields, providing reliable and contactless power readings, which enhances the system's longevity [28]. Power sensors based on the Hall effect principle offer ±1% accuracy. Measurement range up to ±1000 A and ±1000 V is available. They provide non-contact measurement and isolation. However, temperature variations and magnetic field interference can affect measurement accuracy [29].

2.4 Frequency sensor

Frequency sensors continuously monitor the frequency of the microgrid [30]. In AC (alternating current) systems, frequency values must be maintained within a specific standard range (typically 50 Hz or 60 Hz). The grid frequency is monitored to maintain a balance between energy production and consumption. When energy demand increases, the frequency may drop, indicating the need for increased energy production. Frequency sensors detect abnormally low or high frequency conditions and trigger protection systems to prevent damage to equipment. In microgrids connected to the central grid, frequency sensors monitor the frequency differences between the microgrid and the grid, ensuring synchronization. This allows the microgrid to operate in an isolated mode when necessary. Frequency sensors operate with less than 1% error at input frequencies up to 1/10 of their natural frequency. The error rate increases at higher frequencies. The measurement range is 0.1 Hz - 1 MHz. Electromagnetic interference and temperature variations can affect measurement accuracy [31].

2.5 Light sensor

Light sensors are used in solar tracking systems to monitor the movement of the sun and ensure that panels remain in their optimal position. Additionally, in solar power plants, light sensors are employed to monitor system performance. These sensors help in the effective management of energy production. By monitoring shading and light levels, the efficiency of the panels is continuously optimized [32]. The measurement range is from 0.01 lx to 100000 lx and sensitivity down to 0.01 lx (lux) and below is possible. Temperature variations and aging effects can affect measurement accuracy [33].

2.6 Speed sensor

In microgrids, speed sensors are used to measure the velocity of fluids (e.g., air or water) to enhance system efficiency and ensure safety [34]. In renewable energy systems like wind turbines, monitoring wind speed is crucial for improving turbine efficiency. The sensors adjust the turbine's angle based on wind speed, optimizing energy production. In water-based energy generation systems (e.g., hydroelectric plants), speed sensors monitor water flow rates, providing information on how much energy can be generated. This data is transmitted to energy management systems. Speed sensors can operate in measurement ranges from 0 - 10000 RPM and above with error rates of ±0,5% or less. Mechanical vibrations and temperature variations can affect measurement accuracy [35].

2.7 Humidity sensor

Humidity sensors are strategically placed at various points within microgrids to enhance system performance and ensure energy efficiency. Excess humidity can affect the performance of solar panels and wind turbines [36]; by monitoring the surrounding humidity levels, their efficiency can be improved. In battery storage areas, humidity levels are monitored to prevent damage or performance loss caused by excessive moisture. Humidity sensors generally operate with an accuracy of ±2% to ±5% RH. The measurement range is 0% - 100% RH. Temperature influence, contamination and aging can affect the measurement accuracy [37].

2.8 Gas sensor

Gas sensors are essential components used to monitor the presence, concentration, and quality of gases in microgrids [38]. These sensors are strategically placed to enhance the safety, energy efficiency, and environmental monitoring of microgrids. Calibrated gas sensors can provide ±2% accuracy under ideal conditions. However, in some sensors this can be ±25% or more. The accuracy of gas sensors varies depending on the type of sensor and the characteristics of the gas being targeted. For example, ±25% accuracy is acceptable for ozone sensors. Accuracy is in ppm (parts per million) and the measurement range can be 0-10000 ppm (depending on the gas type). It may measure inaccurately due to temperature, relative humidity and sensor aging [39].

Gas sensors are used in microgrids in the following areas:

- Detecting leaks of natural gas, methane, or other potentially harmful gases, reducing the risk of fire or explosion.
- Monitoring air quality, especially in enclosed spaces, by tracking levels of harmful gases (such as carbon monoxide, carbon dioxide, etc.).
- Monitoring the quality and quantity of gas used in fuel systems (e.g., gas generators), ensuring efficient fuel utilization.
- Detecting by-products (such as hydrogen gas) that may form in solar panels or other energy production systems.
- Monitoring emissions in energy production facilities and other industrial areas, helping control harmful gases released into the environment.
- Tracking levels of greenhouse gases, like carbon dioxide, providing data for climate change research.

2.9 Vibration sensor

In microgrids, vibration sensors are important components used to monitor system conditions, identify maintenance needs, and enhance overall safety [40]. Vibration sensors monitor the vibrations of equipment, such as generators, motors, and other moving parts, under normal operating conditions. Abnormal vibration levels allow for the early detection of potential failures. Early diagnosis can prevent large and costly repairs, reducing operational costs. Monitoring vibrations ensures the safe operation of energy production systems and contributes to preventing potential accidents. General purpose vibration sensors operate in the frequency range 30-900000 CPM (0,5-15000 Hz). The accuracy is usually around ±1%. Mounting conditions, environmental factors, noise and mechanical resonances can affect the measurement accuracy [41].

2.10 Acoustic sensor

Acoustic sensors are used in microgrids not directly for energy production or distribution functions, but in supportive areas such as condition monitoring, fault detection, and security. These sensors help improve the performance of the microgrid and detect faults in advance [42].
Acoustic sensors can detect abnormalities by monitoring the sounds and vibrations produced by electrical equipment during operation. For example, faults in a generator, transformer, or electric motor may produce abnormal sounds during operation. These sensors can be used for early warning systems by detecting unusual sound frequencies from equipment.
Some microgrids include large structural components, such as wind turbines or solar panels. In such systems, acoustic sensors are used to monitor the condition of the structures. For instance, damage to wind turbine blades or solar panel mounts can be detected through acoustic emissions.
The accuracy of acoustic sensors varies depending on the frequency range and application area. Usually ±1% accuracy can be achieved. The measurement range is 20 Hz - 20 kHz (20 kHz-10 MHz for ultrasonics). Wind, echo and environmental noise can cause inaccurate measurements [43].

2.11 Pressure sensor

Pressure sensors monitor the pressure of gas or liquid systems within microgrids, and are especially important in hydrogen storage systems. In hydroelectric power generation, controlling water levels and pressure ensures the stability of energy production. Monitoring the internal pressure of energy storage systems enhances safety. In liquid and gas distribution systems, the pressure of fluids (water, air, gas) is monitored to ensure efficient system operation and detect leaks [44]. The types of pressure sensors used in microgrids are listed below:

Analog and Digital Pressure Sensors: These sensors transmit pressure changes as a continuous voltage signal. Typical accuracy is ±0,5% Full Scale (FS). It usually operates with ±0.5% accuracy. It can operate in the measurement range 0 - 1000 bar. Errors such as temperature effect, analog and signal interference can affect the measurement accuracy [45].
Piezoelectric Sensors: These sensors are sensitive to pressure changes and measure pressure using piezoelectric materials. They are typically used in applications that require high precision [46]. Suitable for measuring high frequency pressure changes, especially dynamic pressure changes; accuracy depends on the application. Not suitable for static measurements. Typical accuracies range from 0,2% to 1%. They are resistant to high temperature conditions and can operate up to 500°C. They have fast response at high frequency and low long-term stability [47].
Capacitive Pressure Sensors: Pressure changes are measured by changes in capacitance. These sensors are commonly used in applications that require high accuracy and low power consumption [48]. Capacitive sensors offer high accuracy, typically ±0,1% Full Scale (FS). With low power consumption, they are common in long-term monitoring systems [49].

2.12 Temperature sensor

Temperature sensors are critical for ensuring the safe and efficient operation of energy systems in microgrids [50]. Different types of temperature sensors offer tailored solutions for various applications, enhancing the overall performance of energy systems.

One of the most commonly used temperature sensors in microgrids is found in energy storage systems, particularly in batteries [51]. In battery systems, NTC/PTC thermistors are widely used. Thermistors are high precision temperature sensors. Their typical accuracy is between ±0,1°C and ±0,5°C. They are more accurate in lower temperature ranges, but their accuracy can decrease as the temperature increases [52]. To ensure efficient and long-lasting battery performance, temperature must be kept within a specific range. Overheating can shorten battery life and pose safety risks, such as the potential for fire.
Resistance Temperature Detector (RTD), another type of temperature sensor, has high accuracy (±0,1 °C) and is widely used, especially in industrial environments. Platinum (PT100) type RTDs are the most stable [53]. Thermocouples used in temperature monitoring have a wide temperature range (-200°C to +1300°C). However, their accuracy is around ±1°C and calibration requirements are high [54].

In microgrids, particularly in enclosed spaces or battery rooms, fire risks can arise. Since excessive temperature increases can create fire hazards, temperature sensors are critical for fire safety [55]. When temperature limits are exceeded, these sensors activate fire suppression systems to minimize fire risk.

3. Internet of Things (IoT) Based Sensor Integration

3.1 IoT platforms

IoT platforms are the software and hardware components used to manage data collection, analysis, and control processes for sensors and devices. The key IoT platforms used in microgrids are:

Azure IoT Hub: A service provided by Microsoft, it allows devices to securely connect to a cloud-based system [56]. It offers advanced features such as data analytics and machine learning integration.
Amazon Web Services (AWS) IoT Core: A platform provided by Amazon Web Services [57], it facilitates the easy connection, management, and data exchange of devices in the cloud. It is equipped with security features and data analytics tools.
Google Cloud IoT: Google's cloud-based IoT solution [58] offers comprehensive services for device management, data streaming, and analytics. It also supports integration with machine learning and artificial intelligence.

IBM Watson IoT Platform: A platform offering solutions for industrial IoT applications [59], it provides a comprehensive structure for device connectivity, data collection, and analysis. It is equipped with big data and analytics features.

3.2 IoT protocols

IoT protocols are a set of rules used to ensure data transmission and communication between devices. The key IoT protocols commonly used in microgrids include:

Message Queuing Telemetry Transport (MQTT): A lightweight messaging protocol [60]. It works effectively in environments with low bandwidth and high latency, and is commonly used for collecting and transmitting sensor data.
Constrained Application Protocol (CoAP): A protocol designed for devices with low power consumption and bandwidth requirements [61]. It provides RESTful communication between IoT devices and is commonly used for monitoring environmental data, such as temperature and humidity.
Hypertext Transfer Protocol (HTTP/HTTPS): A widely used protocol on the internet [62]. In IoT applications, it can be used for receiving or sending data from devices. However, due to its high energy consumption, it is less preferred for energy efficiency.
Zigbee: A wireless communication protocol designed for low power consumption and short-range communication [63]. It is commonly used in home automation and industrial IoT applications.
Long Range Wide Area Network (LoRaWAN): A protocol used for long-range communication [64]. It enables data transmission over large areas with low power consumption and is commonly used in agriculture, smart city applications, and environmental monitoring systems.

A comparison of the key characteristics of IoT protocols is given in Table 1.

Table 1. Key characteristics of IoT protocols

Protocol	Latency	Data Rate	Power Consumption	Security Level	Use Care
MQTT	Low	Medium	Very Low	Medium (TLS)	Sensor data collection (real-time) [60]
CoAP	Very Low	Low	Very Low	Medium	Environmental monitoring [61]
LoRaWAN	High	Low	Ultra Low	Low–Medium	Remote rural sensor networks [64]
Zigbee	Low	Medium	Low	High	Short-range control systems [63]
HTTPS	High	High	High	Very High	Secure control interfaces [62]

3.3 Data collection and transmission

For IoT-based sensor integration [65] in microgrids, sensors suitable for the parameters to be measured are selected and placed in suitable locations where data can be collected. Placing the sensors in appropriate locations is critical for accurate data collection Sensors collect data [66] by monitoring in real time. This data is usually recorded at regular intervals or when certain thresholds are exceeded. The collected data is usually stored in a digital format (e.g. JSON, XML). This improves compatibility and accessibility during data transmission. The collected data is transmitted to a centralized system or cloud platform [67] via established data communication protocols. The transmitted data is analyzed and processed and visualized with graphs or panels for easy understanding. Based on the data obtained, necessary measures can be taken. Based on the obtained data, the system can automatically activate control mechanisms to optimize performance.

3.4 Processing of sensor data

Veri işleme, sensörlerden toplanan ham verilerin kullanılabilir ve analiz edilebilir formata dönüştürülmesini kapsar. Mikro şebekelerden toplanan veriler, büyük hacimli ve çeşitli formatlarda olabilir. Bu verilerin işlenmesi aşağıdaki adımları içerir:

Data Filtering and Cleaning: Raw data collected by sensors may contain noise, particularly due to environmental factors. This noise is filtered out using data processing algorithms to improve the data quality [68]. Missing data that might result from sensor errors or connectivity issues can be filled using various techniques (e.g., data prediction algorithms).
Data Transformation: Data received from sensors may be in different formats (e.g., digital or analog). These data are converted into a centralized data format [69]. Data from different sensors are integrated, and the transformed data allows for the evaluation of parameters such as energy production, consumption, weather, and power quality in a unified dataset.
Data Storage: Cleaned and transformed data is stored in a database or cloud system for analysis. In microgrids, large volumes of data are typically stored in distributed databases or data lakes [70]. Data collected from microgrids is often stored in time-series format. This format allows for tracking how dynamic parameters, such as energy production and consumption, change over time.

3.5 Sensor data analysis

Data analysis is the process of transforming processed data into meaningful insights for microgrid operations and management. This step is carried out using various analysis techniques and algorithms [71]:
Descriptive Analysis: Descriptive analysis involves summarizing key information, such as energy production and consumption, grid loads, and power quality, for a specific time period from time-series data. This analysis is used to assess the overall performance of the microgrid. The results of descriptive analysis are typically reported to relevant stakeholders for decision-making.
Diagnostic Analysis: This analysis focuses on identifying deviations and anomalies in the collected data. It helps determine the root causes of system failures or malfunctions. Diagnostic analysis is crucial for fault detection and resolving issues within the microgrid system.
Predictive Analysis: Using IoT-based sensor data, predictive analysis examines the state of machines or equipment before failure. This allows for the creation of proactive maintenance schedules and helps predict potential system faults. Additionally, sensor data is used to forecast future energy demands based on historical consumption data. These predictions are vital for energy production planning.
Optimization Analysis: The data provided by IoT sensors are used to optimize both energy production and consumption. By analyzing real-time data, it is possible to fine-tune energy generation and storage strategies, ensuring that resources are used as efficiently as possible, ultimately enhancing the overall performance of the microgrid.

3.6 Security concerns

IoT-based sensor integration in microgrids brings security and privacy threats. Security measures and privacy policies against these threats are vital for the safe, efficient and sustainable operation of microgrids. The security dimension of IoT-based sensor integration should be addressed at many different layers, from physical security to data security.

Physical Security: Physical damage to sensors can cause corruption of energy data or malfunctioning of other equipment in the system. Physical protection is important against unauthorized access and security measures should be taken against attacks such as physical destruction or the addition of counterfeit sensors.
Network Security: During the transmission of data from sensors to the central management system, the data passing through the network can be vulnerable to attacks [72]. Network attacks, such as man-in-the-middle (MITM) attacks, can result in data being intercepted or altered. Strong encryption algorithms must be used to prevent unauthorized reading or modification of the data transmitted by the sensors. For this, standard encryption techniques such as AES (Advanced Encryption Standard) and RSA are widely used. In addition, each device should be authenticated on the network to prevent unauthorized access and only authorized devices should be allowed to transmit data.
Data Integrity and Accuracy: The data from sensors can be manipulated by malicious actors. For example, energy consumption data may be reported incorrectly, potentially misleading energy management systems. To ensure data accuracy in microgrids, signature verification protocols and error detection algorithms [73] can be employed. These mechanisms allow for the verification of whether the data has been altered after it has been transmitted.

Cyber Attacks: IoT devices in microgrids can be vulnerable to Distributed Denial of Service (DDoS) attacks [74]. These attacks can overload sensors or central systems, leading to service disruptions. To protect against DDoS attacks, security measures such as firewalls and intrusion detection systems should be implemented in microgrids. Continuous monitoring of incoming network traffic is necessary to detect abnormal behavior and mitigate potential threats.

3.7 Privacy concerns

Mikro şebekelerde IoT tabanlı sensörlerin topladığı veriler, kullanıcıların enerji tüketim alışkanlıklarını ve hassas bilgilerini içerebilir. Bu nedenle, gizlilik önemli bir konu haline gelir.
Data Privacy: Data collected through sensors may reveal personal information, such as individuals' energy consumption habits. Protecting such data [75] is crucial for ensuring personal privacy.
Anonymizing user data ensures that personal information cannot be directly linked to individuals. Anonymized data can be used for analysis and reporting purposes while maintaining individual privacy.
Data Sharing: Data collected in microgrids may be shared with energy providers, third-party service providers, or governments. However, during this sharing process, sensitive information should not be disclosed without the owner's consent. Access control mechanisms should be implemented to ensure that IoT-based sensor data in microgrids can only be accessed by authorized individuals and systems [76]. Access should be restricted according to the level authorized by users.
Data Storage and Retention Period: Policies should be established regarding how long the collected sensor data will be stored. Storing data for unnecessarily long periods can lead to privacy violations.
Once the data retention period has expired or when the data is no longer needed, it must be securely destroyed.

3.8 Security and privacy technologies

Various technologies and approaches are used to ensure security and privacy in IoT-based sensor integration in microgrids:
Blockchain Technology: Blockchain technology can be used in microgrids to enhance data security [77]. This technology ensures that data is securely stored and processed, and it provides guarantees regarding the source and accuracy of the data.
Artificial Intelligence (AI)-Assisted Security: AI and machine learning algorithms can detect anomalous data patterns in sensor networks [78]. This plays a significant role in early detection and prevention of attacks.
Data Encryption and Privacy Protocols: New techniques such as homomorphic encryption [79] and differential privacy [80] can be used to increase the privacy of data. These techniques increase the level of confidentiality while enabling data to be analyzed.

4. Ensuring Sensor Accuracy

4.1 Accuracy ensuring techniques

Periodic calibration of sensors [81] is crucial for the accuracy and reliability of energy measurements. Calibration involves the process of comparing the measurements of a device with a known and accepted reference standard. Failure to calibrate leads to misdirection of energy resources due to inaccurate data, incorrect calculation of energy costs, system instability, equipment failures and reduced energy efficiency. Sensor redundancy [82] is a way to ensure accuracy by using multiple sensors at the same measurement point. If one sensor produces inaccurate values, these deviations can be detected by comparing the data from other sensors. This minimizes the impact of failures of a single sensor.
Sensor fusion [83] is a method of combining data from different sensors with the help of algorithms and providing a more reliable measurement based on this data. This technique is used to increase the sensitivity of different parameters in complex systems, especially in microgrids. Also, since environmental conditions (temperature, humidity, pressure, etc.) can affect the accuracy of sensors, sensors that monitor environmental conditions are used in addition to the main sensors. 3.4 to ensure that clean and accurate data is obtained by using the data processing methods specified in clause 3.4. This reduces the effects of sensor failures or transient problems.

Sensors used in microgrids may have a certain margin of error during their lifetime. In order to detect these faults [84] and take corrective measures in advance, algorithms are used to analyze the failure tendencies of sensors, predict and correct possible faults. With regular maintenance and monitoring of sensors, faults due to wear or aging can be detected early. Sensors that wear out or degrade in performance are removed from the system or repaired.

4.2 Challenges in sensor calibration

Accurately calibrating sensors is critical to the effectiveness and reliability of these systems, but calibration processes are not without their challenges.

Various and Dynamic Operating Conditions: The dynamic situation caused by operating conditions, variable environmental factors (light, temperature, wind speed and weather, etc.) and production methods complicate the calibration process of sensors. The high impact of these conditions on the correct operation of the sensors can lead to the need for more frequent calibration.
Different Sensor Types and Applications: Sensors used in microgrids measure very different parameters. Therefore, each type of sensor requires different calibration procedures depending on its sensitivity and accuracy requirements. Integrating the calibration of each sensor is difficult and requires a complex structure.
Local and Remote Distributed Sensors: With wide-area deployment, sensors in local or remote areas can be isolated from each other. It is sometimes difficult to physically access each of these sensors for calibration. When calibration operations have to be performed at remote sites [85], logistical and time problems arise.
Sensor Aging and Wear: The environmental conditions, long-term use and wear and tear effects to which sensors are constantly exposed create deviations in their accuracy and require more frequent calibration.
Long Calibration Intervals and Process Complexity: Long and complex calibration processes can lead to system downtime or performance degradation. Therefore, it is essential to find calibration solutions that do not cause interruptions during the process.
Limitations of Automatic Calibration Methods: Although automatic calibration technologies are advanced, these systems may have limitations in ensuring complete accuracy. While automatic calibration systems may be used for sensors in remote areas, it can be challenging for these technologies to adapt to every sensor type. Additionally, the installation and maintenance of such systems can be costly.
Adapting to Innovative Sensor Technologies: The rapid development of sensor technologies leads to the emergence of new sensor types. However, developing calibration methods suitable for these new technologies may take time and can be difficult to integrate into microgrid systems.

5. Success Stories of Sensor Use in Microgrids

Hawaii Kauai Island Microgrid: Kauai is an island in Hawaii that has developed a microgrid based on renewable energy sources [86]. This microgrid integrates solar energy and energy storage systems to meet the island's energy needs. The sensors used in the microgrid play a critical role in monitoring the energy production from solar panels and managing the energy storage systems. Thanks to the sensors, the balance between energy production and demand has been continuously optimized. As a result, Kauai Island has reduced its energy costs and significantly decreased its use of fossil fuels.
Brooklyn Microgrid: The Brooklyn Microgrid is a microgrid established in New York with the aim of increasing energy independence [87]. This system enables energy trading among homes equipped with solar panels. Sensors monitor the energy production and consumption of each home to manage this trade. This project stands out as an example of using sensors to turn energy consumers into producers and support energy exchanges within local communities. The sensor data has ensured the system remains sustainable and economical by balancing energy supply and demand.
Sendai Microgrid, Japan: After the major earthquake and tsunami in Japan in 2011, a microgrid [88] was established in Sendai City. This microgrid was designed to meet the energy needs of critical infrastructure in emergency situations. Sensors ensure continuous monitoring of the system and enable rapid responses during emergencies. For example, energy consumption sensors and grid status sensors

have made it possible for the microgrid to operate independently from the main grid. The Sendai Microgrid quickly recovered after the disaster, providing energy to the community and demonstrating the importance of sensors in crisis situations.

Stone Edge Farm Microgrid, California: Stone Edge Farm is a vineyard that applies innovative energy solutions in wine production. The microgrid [89] established here includes solar energy, hydrogen fuel cells, and energy storage systems. Sensors optimize the farm's energy management by monitoring energy production, storage status, and consumption levels. The sensor data has been used to meet the farm's energy needs and sell excess energy to the grid. This microgrid has reduced energy costs and increased environmental sustainability.

Loxton Village Microgrid, South Australia: Loxton Village in South Australia, a remote settlement, faced energy supply challenges. The microgrid [90] established here consists of solar energy, wind energy, and energy storage systems. Sensors played a critical role in monitoring local energy production and managing storage systems. This microgrid has increased the village's energy security, reduced energy costs, and decreased reliance on the grid. The data provided by the sensors has enabled the dynamic management of the microgrid and enhanced Loxton Village's energy independence.

6. Future Directions and Innovations

Sensor technologies used in microgrids are rapidly evolving to improve the efficiency of energy systems, optimize energy production and ensure system security. These technologies contribute more to energy management systems (EMS) as sensors become more sensitive, intelligent and communication capable.

6.1 Smart Sensors

Smart sensors are equipped with embedded processors and software to collect, analyze, and process environmental data to generate meaningful information [91], [92]. These sensors collect various environmental data such as temperature, humidity, light, and pressure, and process this data in real-time. Based on the data they collect, they establish automatic control mechanisms within the system. For instance, they can automatically turn on power sources based on energy demand. Smart sensors can transmit the data they collect to energy management systems or cloud platforms via wireless networks [93], enabling integration with a central control system. Smart sensors optimize the balance of supply and demand by monitoring energy flow. For example, they can monitor light levels to improve the efficiency of solar panels. They ensure system safety by detecting excessive temperature, pressure, or power losses. In such cases, they can automatically activate protection circuits. To enhance the efficiency of energy sources, they analyze which resources are used more effectively and can automatically switch between energy sources when needed. By analyzing the data they collect, they identify energy consumption trends [94] and report this data to assist system administrators in decision-making. Smart sensors continuously monitor the system's status and provide the possibility of quick intervention. By automating energy management processes, they reduce human error and increase system efficiency [95]. With the data they collect and process, they enable system administrators to make better decisions [96]. Thanks to remote access, they offer remote monitoring and control capabilities [97].

6.2 Wireless Sensor Networks (WSN)

Wireless sensor networks are emerging as a critical technology to support functions such as energy management and environmental monitoring in microgrids. These are systems in which various sensors are wirelessly connected within a given area to collect and transmit data [98], [99]. These sensors are designed to monitor various variables and send the collected data to a centralized control unit or data processing unit [100]. Wireless communication allows sensors to interact with each other and with the central system without the need for physical connections. Wireless sensors are used in microgrids to monitor energy consumption and production [101]. Data from renewable energy sources such as solar panels and wind turbines are collected [102] and analyzed to improve the efficiency of these sources. Energy management systems (EMS) use this data to balance energy demand and production and support the efficient use of energy resources [103].

Environmental factors such as air quality, temperature, humidity, and noise levels can be monitored through wireless sensors. These data are crucial for enhancing the sustainability of the microgrid and reducing environmental impacts [104]. Wireless sensor networks can be used to improve energy efficiency in lighting, HVAC (heating, ventilation, and air conditioning), and other automatic control systems. Sensors make automatic adjustments based on environmental conditions to minimize energy consumption. For security purposes, wireless sensors can be integrated with motion detectors and camera systems [105]. These sensors create a rapid response mechanism in the event of a security incident, enhancing the security of the microgrid. Thanks to their wireless nature, there is no need for cabling, which reduces installation costs and shortens installation time [106]. This provides significant advantages, especially in hard-to-reach areas or temporary installations. The ease of changing the placement of sensors increases the scalability of the system, making it easier to adapt to future expansion or modification requests [107]. By collecting real-time data, wireless sensors contribute to fast decision-making processes, which is a significant advantage in energy management and environmental monitoring [108]. Most wireless sensors are designed to consume low power, extending their battery life and reducing maintenance needs. This ensures that sensors can operate continuously for long periods. However, wireless communication may be more vulnerable to cyberattacks and data breaches [109]. Therefore, implementing security protocols and continuous monitoring is essential. When large amounts of sensor data are collected, managing and analyzing this data can become complex [110]. This can affect the performance and efficiency of data processing units. The range limitations of sensors [111] can impact the coverage area of the network. This can be a problem, especially when sensors need to be distributed over large areas.

6.3 IoT Based Sensors

The Internet of Things (IoT) is a technology that enables sensors to work together and integrate with other devices over the internet, playing a significant role in microgrids [112]. IoT-based sensors offer great benefits for the continuous monitoring and management of microgrid systems. IoT sensors transmit data to cloud-based platforms, where this data is processed in real-time. Sensors integrated with IoT provide detailed information about energy consumption and production. These IoT sensors allow for better analysis of the system and enable detailed processing of data for energy efficiency.

6.4 Fiber Optic Sensors

Optical sensors used in microgrids are devices that evaluate environmental conditions by detecting light levels, wavelengths, or the light spectrum [113], [114]. They typically include components such as photodiodes, phototransistors, and photoresistors, providing information about the presence, intensity, or quality of light. Optical sensors collect essential data for energy consumption and production by detecting light levels in the environment. The collected light data is then analyzed and used to optimize the system’s energy management strategies. For example, they can automatically adjust the orientation of solar panels based on the amount of sunlight, making real-time adjustments according to the light conditions in the environment. These sensors also allow system administrators to monitor the system remotely [115].

6.5 Digital Twin Technology Integrated Sensors

Digital twin technology [116] enables the creation of virtual models of physical entities, making real-time data flow possible. Sensors used in microgrids, when integrated with digital twins, allow for the early detection of potential issues in the system and the simulation of the energy production process. Digital twins create a virtual replica of the system using sensor data, enabling real-time monitoring, maintenance, and optimization. This technology helps by predicting failures in advance, ensuring more efficient operation of the system's sensors, reducing maintenance costs, and improving production processes.

6.6 Autonomous Sensor Systems

Autonomous sensor systems are sensors that can calibrate themselves, optimize energy consumption, and respond to abnormalities in the system without the need for external intervention [117]. Equipped with advanced software and artificial intelligence, they have self-learning and calibration capabilities. They continuously optimize system performance. These sensors detect faults in the system without human intervention and make the necessary corrections, thereby ensuring more efficient and secure energy management.

6.7 Energy Harvesting Sensors

Energy harvesting sensors operate by collecting energy from environmental sources [118]. These sensors can power themselves using energy obtained from sources such as sunlight, heat, or vibrations, creating an energy-independent system. These sensors are especially useful in areas where powering the system is challenging, such as remote locations, and they provide long-term, sustainable operation by utilizing environmental energy sources. Energy-independent sensors reduce costs, decrease maintenance, and offer significant advantages in energy management for remote areas.

7. The Future of Sensors in Microgrids

Sensor technologies in microgrids are among the key components that will enable more efficient, flexible, secure and sustainable operation of systems in the future. Smart sensors will provide autonomous management and proactive intervention in microgrids by integrating with artificial intelligence, IoT, wireless networks and advanced security protocols. Sensors of the future will be able to detect system anomalies, self-calibrate, react autonomously, minimize human intervention and reduce maintenance costs. By analyzing sensor data with artificial intelligence and machine learning, failures will be predicted, energy production will be optimized, and carbon emissions will be reduced. Thanks to IoT-based systems, real-time data collection and analysis will be possible, and the energy production-consumption balance will be monitored instantly.Wireless sensor networks (WSN) will make it possible to spread over larger areas at low cost, while energy harvesting technologies will enable sensors to generate their own energy and become more sustainable. 5G and similar communication technologies will enable fast and reliable operation of sensors with low latency and high data rates, enabling instant response to emergencies. The increasing number of connected devices makes cyber security critical. In this context, strong security protocols and solutions such as blockchain will protect data integrity. In addition, within the scope of combating climate change, sensors will contribute to the environmental sustainability of microgrids by monitoring environmental parameters such as temperature, humidity and air quality more precisely.

8. Conclusion

This study has shown that sensor technologies significantly improve the reliability, efficiency and resilience of microgrids. Sensor technologies in IoT-based microgrids not only contribute to the optimization of existing systems, but also play a key role in building sustainable, smart and resilient energy infrastructures. Thanks to their functions such as real-time data collection, monitoring energy consumption and generation patterns, and early detection of system failures, sensors increase energy efficiency, reduce costs and strengthen system security.

Analyzing sensor data with artificial intelligence and machine learning algorithms provides insights that turn into decision support systems in energy management, enabling microgrids to operate more flexibly and efficiently. The effective use of sensors in load management, demand response strategies and optimization of renewable energy sources (solar, wind, etc.) makes significant contributions to ensuring energy supply-demand balance and reducing environmental impacts. Case studies such as the Sendai and Kauai microgrids have shown that sensor-driven architectures reduce energy costs and increase disaster resilience.

However, there are some limitations to the widespread adoption of these technologies. Technical challenges such as energy consumption of sensors, reliability of communication infrastructures, data security, system integration and hardware resilience are among the key issues that still need to be addressed. In addition, real-time and secure processing of large data sets requires high processing power and advanced algorithms.

Future research should specifically focus on the following areas:

- Development of energy harvesting and low power consumption sensor systems
- Artificial intelligence supported sensor architectures that can make autonomous decisions
- Advanced automation systems in demand response applications
- Effective management of sensor data with cloud and edge computing integration
- Development of smart interfaces that analyze and guide user behavior

As a result, sensor technologies not only improve technical system performance, but also contribute to the spread of sustainability awareness by increasing the awareness of energy users. Smart sensor systems integrated into microgrids are positioned as one of the basic building blocks of the environmentally friendly, digital and flexible energy systems of the future.

Limitations

This study is limited by the lack of primary simulation or experimental validation. While the literature review is extensive, experimental tests or prototype implementations could further validate the findings. Performance metrics of the sensors (e.g. accuracy, latency, energy consumption) were synthesized from secondary sources; actual values may vary under different operating conditions. In addition, the cybersecurity analyses are theoretical and practical threat modeling is proposed for future work.

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