



National Technical and Economic Potential of Low-Grade Industrial Waste-Heat Power Generation in the United States: A Sector-Level Assessment Benchmarked to DOE and EIA Data

Manam Ahmed¹;

- [1]. Independent Researcher, Mechanical Engineering and Sustainable Energy Systems, USA;
M.Eng. in Mechanical Engineering, Lamar University, Beaumont, Texas, USA
B.Eng. (Hons.) in Mechanical Engineering, Universiti Teknologi Malaysia, Malaysia;
Email: manam.ahmed1996@gmail.com

Doi: [10.63125/0mx67m85](https://doi.org/10.63125/0mx67m85)

Received: 11 March 2026; Revised: 17 April 2026; Accepted: 05 May 2026; Published: 10 June 2026;

Abstract

Low-grade industrial waste heat is a large but difficult-to-quantify U.S. energy resource because national energy statistics measure fuel consumption and end uses more directly than recoverable heat streams at specific temperatures. This study develops a transparent sector-level methodology for estimating the technical and economic potential of electricity generation from industrial waste heat below 150 °C while explicitly separating measured federal data from engineering assumptions. Final 2022 Manufacturing Energy Consumption Survey data from [U.S. EIA \(2026a\)](#) provide the manufacturing fuel-consumption basis, while the national waste-heat temperature inventory of [U.S. DOE \(2008\)](#), the DOE Manufacturing Energy and Carbon Footprints, the DOE waste-heat-to-power benchmark, and current electricity-price information provide external constraints. The model assigns sector-specific sub-150 °C waste-heat fractions and representative temperatures as explicit scenario parameters rather than treating them as DOE or EIA observations. Under the base case, 15,742 TBtu/yr of manufacturing fuel consumption yields a modeled gross sub-150 °C waste-heat resource of 724 TBtu/yr. After temperature-dependent capture and net conversion assumptions, this corresponds to 5.60 TWh/yr and 853 MW of technical nameplate potential at a 75% capacity factor. Chemicals, paper, petroleum and coal products, and food account for the majority of the modeled resource. A source-temperature-dependent capital-cost screen, 20-year project life, 7% discount rate, 2.5% annual fixed O&M, and the 2025 U.S. average industrial electricity price of 8.62 cents/kWh produce a base economic potential of approximately 494 MW. Monte Carlo propagation gives a 5th–95th percentile technical range of 579–1190 MW and an economic range of 262–693 MW. The study therefore provides a reproducible national screening framework rather than a claim of site-level project readiness. Results indicate that low-grade waste-heat power is smaller than DOE's high-temperature WHP technical benchmark but can still represent a material distributed generation opportunity if project costs, operating hours, and source temperatures are favorable.

Keywords

Industrial Waste Heat; Waste Heat to Power; Organic Rankine Cycle; Low-Grade Heat; Manufacturing Energy Consumption Survey; Technical Potential; Economic Potential;

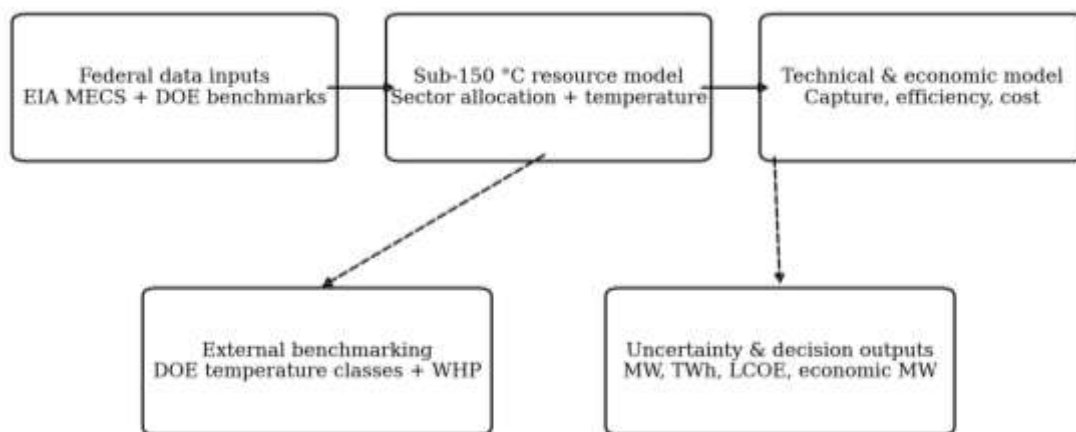
INTRODUCTION

Industrial thermal processes reject energy through exhaust gases, warm liquids, cooling systems, product streams, condensers, dryers, ovens, furnaces, compressors, and process integration gaps. The quantity of this rejected heat is substantial, but its usefulness depends strongly on temperature. [U.S. DOE \(2008\)](#) estimated 1,478 TBtu/yr of unrecovered industrial waste heat relative to a 25 °C reference and classified 903 TBtu/yr within a broad low-temperature class below 230 °C. The same assessment emphasized that low-temperature heat is lower in thermodynamic quality but large in aggregate magnitude, with a reported work potential of 287 TBtu/yr for the broad low-temperature class. That national evidence establishes the scale of the resource while also exposing the difficulty of translating a thermal inventory into realizable electric capacity.

The present study narrows the analytical scope to heat sources below 150 °C. This definition is deliberately more restrictive than DOE's <230 °C low-temperature category. The boundary is selected because sub-150 °C recovery represents one of the most difficult power-generation regimes: conventional steam systems are generally unattractive, available temperature differences are small, equipment cost per kilowatt rises, and net conversion efficiency is low. Organic Rankine cycle (ORC) systems and related binary-cycle technologies are therefore central to the technical discussion. Reviews by [Tchanche et al. \(2011\)](#), [Vélez et al. \(2012\)](#), [Quoilin et al. \(2013\)](#), [Lecompte et al. \(2015\)](#), and [Loni et al. \(2021\)](#) consistently identify ORC technology as a principal option for low-grade heat-to-power conversion, while also emphasizing working-fluid selection, heat-exchanger design, part-load behavior, minimum economical scale, and capital cost.

A second difficulty is data structure. [U.S. EIA \(2026a\)](#) reports that the final 2022 Manufacturing Energy Consumption Survey is now available and identifies chemicals, petroleum and coal products, paper, and primary metals as the dominant manufacturing energy users. MECS is an unusually strong national activity dataset, but it does not directly provide a measured inventory of recoverable waste heat below 150 °C for every NAICS sector. DOE's Manufacturing Energy and Carbon Footprints, based on MECS data and engineering assumptions, map fuel, electricity, steam, end uses, and losses for major manufacturing sectors and are useful for interpreting where recovery opportunities may occur ([U.S. DOE, 2021a](#)). A credible national assessment must therefore avoid silently converting fuel consumption into "waste heat." The conversion requires an explicit model.

Figure 1: National Assessment Framework for Sub-150 °C Industrial Waste-Heat Power



This paper develops such a model. It is a hybrid top-down and engineering-screening methodology. EIA fuel consumption is used as the measured sector activity basis; DOE waste-heat and energy-loss studies provide national and process-level benchmarks; source-temperature, capture, conversion-efficiency, capital-cost, and site-realization parameters are introduced transparently as scenario assumptions. The result is not intended to replace plant audits. Instead, it estimates the scale, sector concentration, cost sensitivity, and uncertainty of a national sub-150 °C waste-heat-to-power opportunity using a reproducible calculation chain.

The study is also designed to prevent a common methodological error in national potential studies: mixing quantities that use different boundaries. DOE's 2021 waste-heat-to-power fact sheet states that 938 MW of WHP was installed at more than 100 U.S. sites as of 2019 and that a 2016 DOE bottom-up analysis identified 8,840 MW of technical WHP potential from 2,946 sites. However, that technical-potential study examined industrial waste streams above 450 °F, approximately 232 °C (U.S. DOE, 2021b). It therefore cannot be treated as a direct estimate of sub-150 °C potential. In this study it is used only as an external scale benchmark.

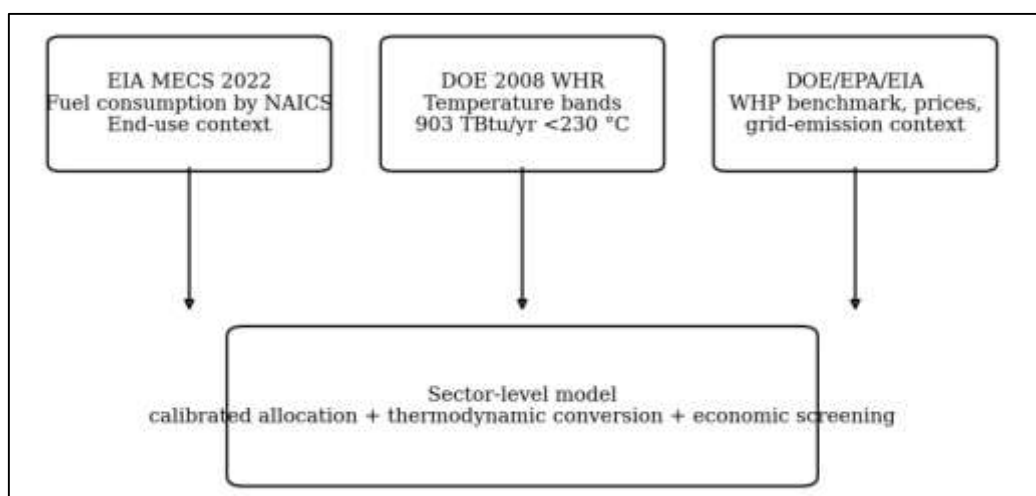
Background of the Study

U.S. manufacturing is heterogeneous in both energy scale and thermal-process structure. Petroleum refining and chemicals consume very large quantities of fuel, but much of their thermal demand occurs at temperatures well above the low-grade range. Food, beverage, paper, textile, wood, and many finishing operations often contain large streams of warm water, dryer exhaust, evaporator and condenser duty, and process cooling that are lower in temperature but potentially more compatible with binary power systems. Primary metals and nonmetallic minerals also have major heat losses, although a large share originates in high-temperature furnaces, kilns, and hot products. These differences mean that a national assessment cannot rank sectors solely by total fuel use.

The DOE energy footprints provide an important conceptual bridge between energy use and recoverable loss. U.S. DOE (2021a) states that its 15 sector footprints cover approximately 95% of manufacturing primary energy use and map energy through boilers, process heaters, process coolers, machine-driven equipment, HVAC, and other end uses. The associated definitions document also publishes sector-specific process-heating loss assumptions; for example, the estimated process-heating energy loss fractions range widely among sectors. Those values are not themselves sub-150 °C waste-heat fractions, but they demonstrate why sector structure must be represented explicitly rather than with a single national percentage.

Economically, low-grade power recovery occupies a difficult region between energy efficiency and distributed generation. The heat itself may have essentially zero fuel cost because it is a process byproduct, but the electricity is not free: heat exchangers, pumps, expanders, condensers, controls, working fluid, civil integration, fouling management, and outage-related installation all create capital and operating costs. Historical reviews by Vélez et al. (2012) and Quoilin et al. (2013) report broad cost ranges and strong scale effects for ORC systems. Accordingly, this study treats capital cost as a sensitivity variable rather than as a universally fixed technology price.

Figure 2: Data Lineage and Evidence Separation in the Assessment



Problem Statement

The United States has multiple authoritative datasets related to industrial energy and waste heat, but no single federal table directly answers the question posed by this study: how much electricity could be generated technically and economically from industrial waste heat below 150 °C, by manufacturing

sector, under a consistent national methodology? EIA MECS provides high-quality energy-use data but not a direct sub-150 °C waste-heat inventory. DOE provides waste-heat temperature benchmarks and sector energy-loss frameworks, but the major national WHP technical-potential estimate is focused on substantially hotter streams. Academic ORC literature provides thermodynamic and cost relationships, but most studies are plant- or technology-specific. The research problem is therefore one of data integration, boundary consistency, transparent assumptions, and uncertainty.

Purpose and Objectives of the Study

The purpose of the study is to develop and apply a transparent, reproducible methodology for screening the U.S. national technical and economic potential of sub-150 °C industrial waste-heat power generation at the sector level. The specific objectives are to: (1) establish a current manufacturing energy baseline using final 2022 MECS data; (2) benchmark the modeled low-grade thermal resource to DOE national waste-heat evidence; (3) estimate technical electricity generation and nameplate capacity using temperature-dependent capture and conversion parameters; (4) evaluate sector-level economic potential using a source-temperature-dependent capital-cost screen and current industrial electricity value; (5) quantify sensitivity to electricity price, capital cost, low-grade allocation, capture, conversion efficiency, and operating utilization; (6) estimate the uncertainty interval of national results; and (7) compare the resulting scale with DOE's existing WHP deployment and high-temperature technical-potential benchmarks without conflating their scopes.

Research Questions

RQ1: What is the modeled gross sub-150 °C industrial waste-heat resource when final 2022 EIA manufacturing fuel consumption is used as the sector activity basis?

RQ2: How is technical low-grade waste-heat power potential distributed among major U.S. manufacturing sectors?

RQ3: How do source temperature, heat-capture fraction, net conversion efficiency, and operating utilization influence national technical potential?

RQ4: What share of technical potential is economically screened under alternative installed-cost and avoided-electricity-value scenarios?

RQ5: How do the modeled sub-150 °C results compare with DOE's broader low-temperature waste-heat inventory and its separate high-temperature WHP technical-potential benchmark?

Research Hypotheses

H1: The absolute technical potential is concentrated in a small number of high-energy sectors, particularly chemicals, paper, petroleum and coal products, and food manufacturing.

H2: Sector economic attractiveness is jointly determined by energy scale and source temperature; therefore, the sectors with the highest fuel consumption will not necessarily have the lowest levelized electricity cost.

H3: Economic potential responds nonlinearly to avoided electricity value and installed cost because low-temperature projects cluster near a cost threshold.

H4: A sub-150 °C national technical-potential estimate will be materially lower than DOE's 8,840 MW benchmark for industrial waste streams above 450 °F because the present temperature boundary is more restrictive and conversion efficiencies are lower.

Significance of the Research

The study is significant for industrial energy analysts because it provides a reproducible way to translate federal energy statistics into a bounded heat-to-power screening result without presenting assumptions as measurements. It is significant for technology developers because it identifies the sectors and temperature ranges in which low-grade ORC cost reductions can have the greatest national effect. It is significant for policymakers because it clarifies that national "waste heat" and national "waste heat to power" estimates depend strongly on temperature boundary, reference temperature, site count, and technology assumptions. Finally, it is significant for academic research because it demonstrates a data-governance approach in which federal observations, engineering calibrations, and scenario assumptions are separately labeled and propagated through uncertainty analysis.

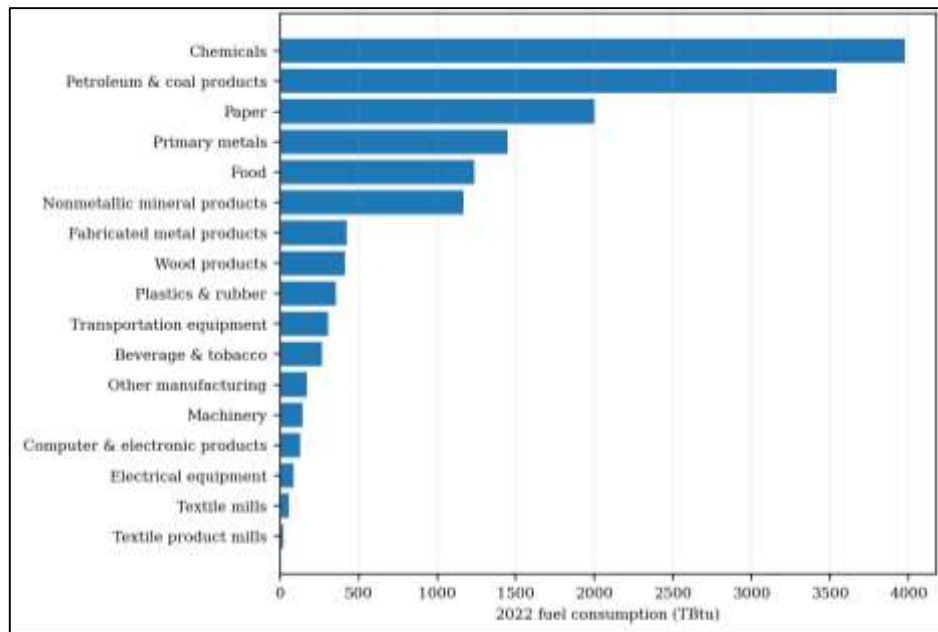
LITERATURE REVIEW

U.S. Manufacturing Energy Baseline

Final 2022 MECS results provide the most current comprehensive federal manufacturing energy baseline for the analysis. [U.S. EIA \(2026a\)](#) states that the final data were released on March 18, 2026 and that the earlier consumption and end-use release identified four subsectors, chemicals, petroleum and coal products, paper, and primary metals—as accounting for most manufacturing energy consumption. Table 5.2 of the 2022 MECS provides fuel consumption by manufacturing industry and end use in trillion Btu. The national total used in the present model is 15,742 TBtu of fuel consumption.

MECS is suitable as an activity basis because it is specifically designed to provide national estimates of manufacturing energy characteristics. The 2022 data page organizes fuel consumption, end-use consumption, nonfuel use, fuel switching, economic variables, building counts, and energy-management information by industry and region ([U.S. EIA, 2026b](#)). Nevertheless, fuel input remains distinct from waste heat. Boiler fuel, process-heating fuel, machine-drive energy, and other uses produce different loss pathways and temperature distributions. The sector conversion factors introduced later in this paper therefore represent model calibration parameters, not hidden transformations embedded in MECS.

Figure 3: EIA 2022 MECS Sector Fuel Consumption Used in the Study



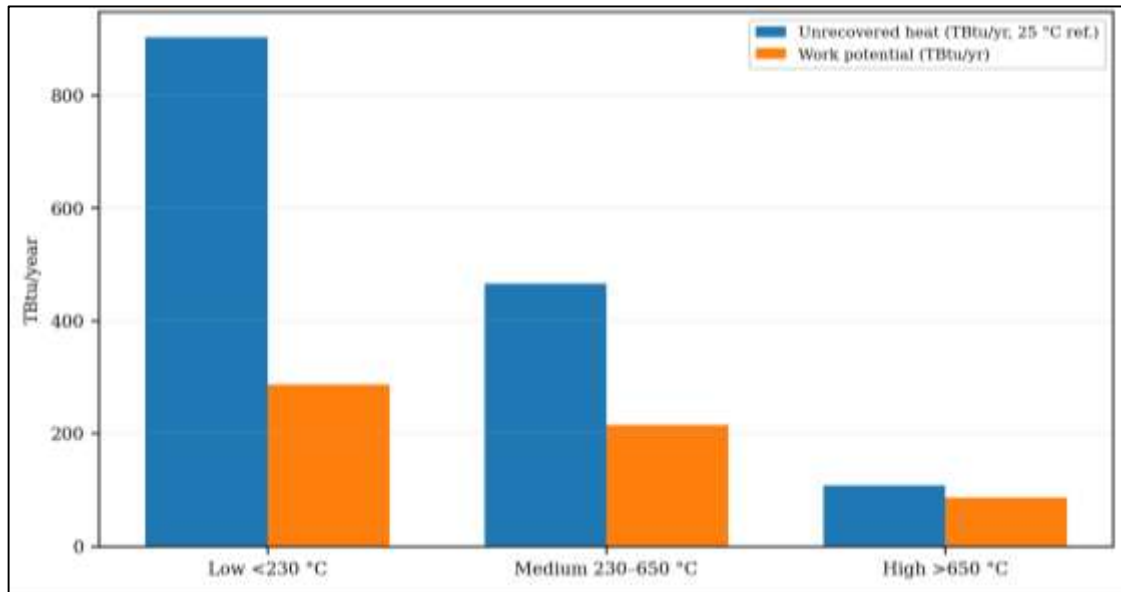
Federal Waste-Heat Benchmarks

The most important federal thermal benchmark for this study is the 2008 DOE waste-heat recovery assessment. [U.S. DOE \(2008\)](#) estimated 903 TBtu/yr of unrecovered heat in the “low” class below 230 °C, 466 TBtu/yr in the 230–650 °C class, and 108 TBtu/yr above 650 °C when measured against a 25 °C reference. Corresponding work potentials were 287, 216, and 86 TBtu/yr. DOE also reported a much smaller 37 TBtu/yr low-temperature quantity when a 150 °C reference temperature was used, which illustrates the sensitivity of “waste heat” magnitude to reference conditions. The present paper does not equate that 37 TBtu number with heat physically below 150 °C; it is a reference-temperature calculation, not a temperature-bin inventory ([Debasish, 2021](#); [Md. Abdur & Iftekhar, 2021](#)).

The DOE report also identifies common low-temperature sources such as warm exhaust, process liquids, compressor cooling, drying and baking ([Debasish, 2022](#); [Md Ashfaq & Abdullah Mohammad, 2022](#); [Md Asif Ali Sheak & Risha, 2022](#)), and other streams where ORC or Kalina technologies can be considered. It emphasizes that lower temperature differences increase heat-exchanger area and reduce economic attractiveness. Those observations are directly relevant to the capital-cost gradient used later in the economic model ([Md. Rashedul & Md Kaium, 2022](#); [Mohammad Abir Chowdhury & Tonay, 2022](#); [Mohammad Shoriful Hossan, 2022](#)). A separate benchmark is the DOE waste-heat-to-power fact sheet. [U.S. DOE \(2021b\)](#) reports 938 MW of installed WHP at more than 100 U.S. sites as of 2019 and cites a 2016 analysis identifying 8,840 MW from 2,946 industrial sites. Critically, that analysis covered waste streams above 450 °F. It is therefore a

benchmark for the scale of established/higher-temperature WHP opportunity, not an estimate of the sub-150 °C opportunity developed here (Mst Kaniz, 2022; Nishat & Mst Kaniz, 2022; Shaiful et al., 2022).

Figure 4: DOE Waste-Heat Inventory and Work-Potential Benchmark by Temperature Class

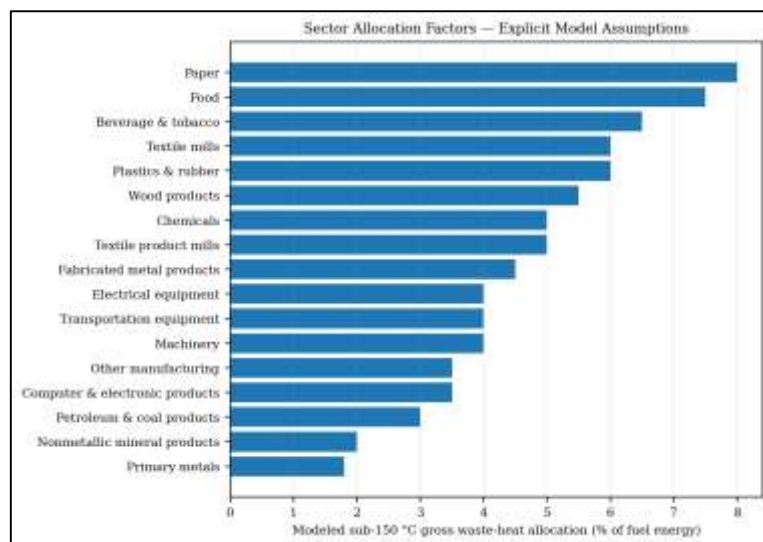


Source: plotted from U.S. DOE (2008),

Industrial Energy Losses and Sector Heterogeneity

The DOE Manufacturing Energy and Carbon Footprints provide a complementary sector framework. U.S. DOE (2021a) explains that 15 manufacturing footprints account for approximately 95% of U.S. manufacturing primary energy use and map energy to boilers, process heating, machine drives, process cooling, facilities, onsite generation, and associated losses (Abdullah Mohammad, 2023; Debasish, 2023; Md Kaium, 2023).

Figure 5: Sector-Specific Sub-150 °C Waste-Heat Allocation Factors Used in the Model



The footprints are valuable because they demonstrate that energy loss is not distributed uniformly across industries or end uses (Md Mahamud Pervaz, 2023; Mohammad Abir Chowdhury, 2023; Mohammad Badrul & Md. Mominul, 2023). The associated definitions document reports a 33% weighted-average process-heating loss assumption across manufacturing but substantially different sector values. Food and beverage, forest products, textiles, glass, foundries, and other sectors can exhibit high process-heating loss fractions, while petroleum refining and chemicals show different energy-loss structures (Ashrafuzzaman, 2024; Debasish, 2024; Nishat,

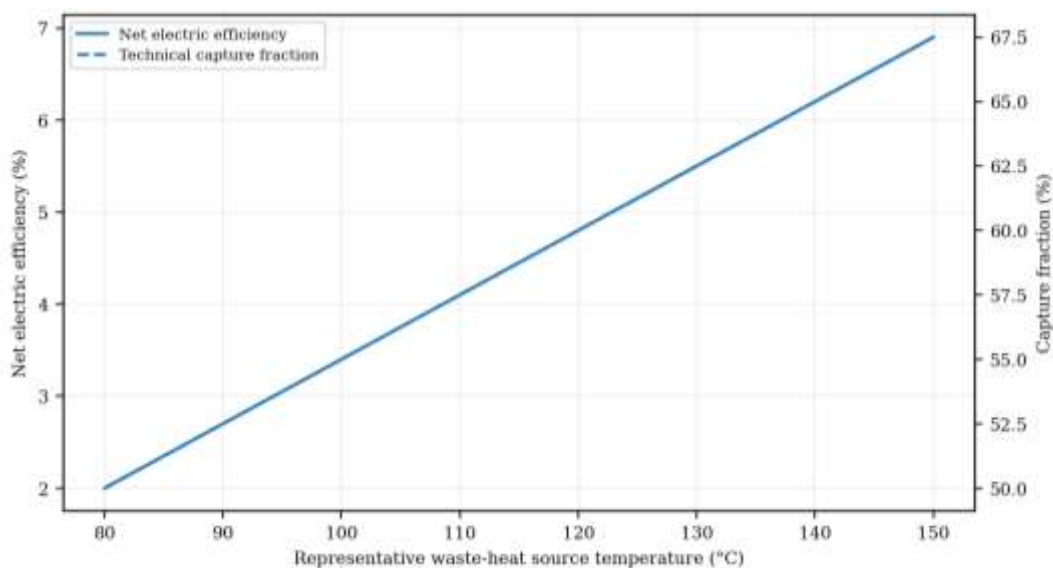
2023). Those figures cannot be directly converted into sub-150 °C thermal availability because loss temperature is not specified for each component. However, they support the use of sector-specific rather than universal low-grade allocation factors (Md Anisur Rahman, 2024; Md Kaium, 2024).

Low-Grade Heat-to-Power Technologies

Low-grade heat can be upgraded to useful heat, directly reused, stored, converted to cooling, or converted to power. Power generation is only one competing use and is usually less thermodynamically efficient than direct heat recovery. The present study focuses on power because electricity is highly fungible and can be used onsite, but it should not be interpreted as a recommendation to generate electricity whenever a higher-value thermal reuse exists (Md. Shakhawat & Md, 2024; Nishat & Jahanara, 2024).

ORC systems dominate the low-grade power literature because organic working fluids permit evaporation and expansion at lower temperatures than conventional steam systems (Debasish, 2025a; Tonay et al., 2024; Uddin & Risha, 2024). Tchanche et al. (2011) reviewed applications across geothermal, solar, biomass, and waste heat and described ORC technology as increasingly important for low-temperature conversion. Vélez et al. (2012) reviewed technical, economic, and market conditions and documented substantial cost variation with plant size. Quoilin et al. (2013) similarly emphasized decentralized low-temperature power generation, working-fluid selection, expander design, pinch constraints, and minimum economical scale. Lecompte et al. (2015) reviewed advanced ORC architectures for waste-heat recovery and emphasized the need to state boundary conditions consistently because reported performance is highly dependent on source conditions and assumptions. Loni et al. (2021) synthesized industrial ORC waste-heat recovery studies and concluded that waste heat can support efficient power generation while identifying continuing challenges in system selection, economics, and integration. These findings motivate the source-temperature-dependent rather than constant conversion efficiency used in the present model (Debasish, 2025b; Jannatul, 2025; Md Anisur Rahman, 2025).

Figure 6: Temperature-Dependent Capture and Net Conversion Assumptions



Economic and Decarbonization Context

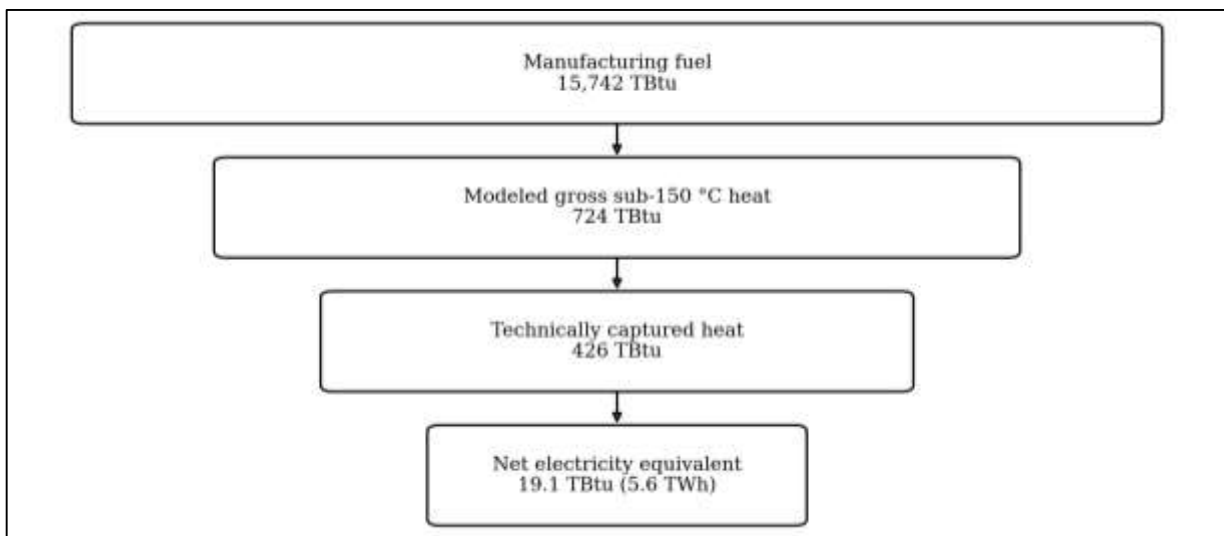
Industrial electricity value is a central economic variable because a behind-the-meter WHP project can offset purchased electricity. U.S. EIA (2026c) reports a 2025 U.S. annual average industrial retail electricity price of 8.62 cents/kWh. That national average is used only as a reference screen. Actual economic value can be lower or higher depending on state, tariff, demand charges, time-of-use structure, wholesale exposure, export compensation, and whether the generated electricity changes peak demand (Md Arif Uz et al., 2025; Md Kaium, 2025; Md Mahamud Pervaz, 2025). DOE's Industrial Decarbonization Roadmap treats energy efficiency and waste heat recovery as cross-cutting industrial decarbonization strategies and identifies low-temperature waste heat to power among relevant technology opportunities (U.S. DOE, 2022). Waste-heat power does not require additional combustion at the conversion unit, so its operational emissions are primarily associated with the underlying process and lifecycle equipment rather than incremental fuel use (Mohammad Abir Chowdhury, 2025; Mohammad Badrul, 2025; Nishat, 2025). For an order-of-magnitude emissions screen, the present paper applies the 2024 U.S. average electric-power CO₂ output rate of 785 lb/MWh reported by U.S. EIA (2025). This

is an average-grid displacement indicator, not a marginal dispatch emissions factor (Nuzhat Sadia, 2025; Sadia, 2025; Tonay, 2025).

THEORETICAL AND CONCEPTUAL FRAMEWORK

The framework consists of four sequential potentials. Resource potential is the modeled thermal quantity below 150 °C. Technical potential is the electricity that can be produced after applying recoverability, capture, and net conversion assumptions. Economic potential is the portion of technical capacity that passes a levelized-cost/avoided-value screen after accounting for site realization. Deployment potential is the project capacity that would actually be built after plant-specific engineering, permitting, reliability, financing, ownership, outage, and organizational constraints. This paper quantifies the first three and does not claim to estimate final deployment. The use of a four-stage framework is essential because the ratios between stages are not constants. A sector can have abundant low-grade heat but weak technical conversion if temperatures are too low. Another sector can have moderate heat but strong economics because operating hours are high, source temperature is favorable, and the system is large enough to achieve low specific cost. National screening should therefore retain both thermal quantity and heat quality.

Figure 7: National Energy-Conversion Funnel under Base-Case Assumptions



Governing Equations

For sector s , gross sub-150 °C waste heat is estimated as:

$$Q_{LG,s} = E_{fuel,s} \times \lambda_s$$

where $E_{fuel,s}$ is 2022 MECS fuel consumption and λ_s is the explicit sector low-grade allocation factor.

Technically captured heat is:

$$Q_{cap,s} = Q_{LG,s} \times f_{cap}(T_s)$$

Annual net electricity is:

$$E_{el,s} = Q_{cap,s} \times 293.071 \text{ GWh/TBtu} \times \eta_{net}(T_s)$$

Nameplate technical capacity at capacity factor CF is:

$$P_{tech,s} = E_{el,s} / (8,760 \times CF)$$

The capital recovery factor is:

$$CRF = r(1+r)^n / [(1+r)^n - 1]$$

The simplified levelized cost of electricity is:

$$LCOE_s = [C_s \times CRF + FOM_s] / (8,760 \times CF)$$

Economic capacity is represented as a soft screening function rather than a hard cutoff:

$$P_{econ,s} = P_{tech,s} \times f_{site} \times \{1 / [1 + \exp(-(V_e - LCOE_s)/k)]\}$$

where f_{site} represents non-cost site realization, V_e is avoided electricity value, and k controls the smoothness of the economic threshold.

METHODS

Research Design and Scope

The study is a national sector-level scenario assessment using a hybrid top-down/engineering methodology. It covers NAICS manufacturing sectors and defines low-grade waste heat as heat with a representative source temperature below 150 °C. The model uses annual national quantities and therefore does not identify individual plants, specific waste streams, hourly coincidence, or local interconnection conditions.

The principal measured input is 2022 sector fuel consumption from EIA MECS Table 5.2. Seventeen sector groups are represented; the “Other manufacturing” category is a residual that reconciles the sector list to the 15,742 TBtu national total. The measured fuel quantity is then passed through sector-specific allocation factors to estimate gross low-grade heat. These factors are intentionally published in the manuscript so another researcher can substitute different factors and reproduce the consequences.

Table 1. Sector Activity Data and Explicit Low-Grade Modeling Assumptions

Sector	NAICS	2022 fuel (TBtu)	Modeled low-grade fraction	Representative T (°C)
Food	311	1,235	7.5%	105
Beverage & tobacco	312	265	6.5%	100
Textile mills	313	57	6.0%	110
Textile product mills	314	21	5.0%	100
Wood products	321	414	5.5%	105
Paper	322	2,003	8.0%	115
Petroleum & coal products	324	3,543	3.0%	125
Chemicals	325	3,976	5.0%	120
Plastics & rubber	326	357	6.0%	100
Nonmetallic mineral products	327	1,166	2.0%	125
Primary metals	331	1,449	1.8%	130
Fabricated metal products	332	425	4.5%	105
Machinery	333	143	4.0%	100
Computer & electronic products	334	128	3.5%	90
Electrical equipment	335	87	4.0%	100
Transportation equipment	336	304	4.0%	100
Other manufacturing	Residual	169	3.5%	95

Sector Low-Grade Allocation

Allocation factors were selected to reflect three constraints. First, the national total should remain below DOE’s broader <230 °C low-temperature inventory because the present temperature boundary is narrower. Second, sectors with extensive low-temperature drying, evaporation, condensation, warm-liquid, or process-cooling loads receive larger factors than sectors dominated by very high-temperature furnaces and kilns. Third, no factor is treated as a direct measurement. In the base case, allocation factors range from 1.8% for primary metals to 8.0% for paper, producing a national gross sub-150 °C resource of approximately 724 TBtu/yr, or 4.6% of manufacturing fuel consumption. This is about 80%

of DOE's broader 903 TBtu/yr <230 °C thermal benchmark.

Technical Conversion Model

The technical model uses a representative source temperature for each sector and applies temperature-dependent capture and net electric efficiency. Capture fraction increases from approximately 50% at 80 °C toward the upper-60% range near 150 °C, reflecting improved heat-exchanger driving force and the ability to cool useful streams through a larger effective temperature span. Net electric efficiency is represented as approximately 2% at 80 °C and approaches 7% near 150 °C. These values are not proposed as universal ORC performance. They are transparent national-screening assumptions chosen to remain physically plausible relative to low-grade ORC literature.

Annual electricity is converted to technical nameplate capacity using a 75% capacity factor. This value represents continuous-process industrial availability with allowance for outages, maintenance, source variability, and non-coincident operation. A sensitivity case is included because actual utilization can be materially lower at batch facilities or higher for continuously operating process plants.

Economic Screening Model

The economic model is intentionally simple enough to audit. Installed cost is expressed per net electric kilowatt and decreases with source temperature: the base curve ranges from approximately \$6,500/kW at 80 °C to \$2,400/kW at 150 °C in constant 2025 dollars. The curve captures the fact that very low-temperature systems require larger heat-transfer surface and more equipment per unit of electric output. It is informed by the qualitative and historical cost behavior described in ORC literature and DOE documents, but it is not presented as a current vendor quote.

Projects are evaluated over 20 years at a 7% real discount rate with fixed O&M equal to 2.5% of installed capital per year. The national 2025 average industrial retail price of 8.62 cents/kWh from [U.S. EIA \(2026c\)](#) is used as the base avoided-value reference. Because actual tariffs differ widely, results are also calculated from 5 to 12 cents/kWh. A 65% site-realization factor is applied before the economic screen to represent non-price constraints such as space, process ownership, fouling, outage coordination, source continuity, interconnection, and project-development friction.

Figure 8: Source-Temperature Cost Curve Used for National Economic Screening

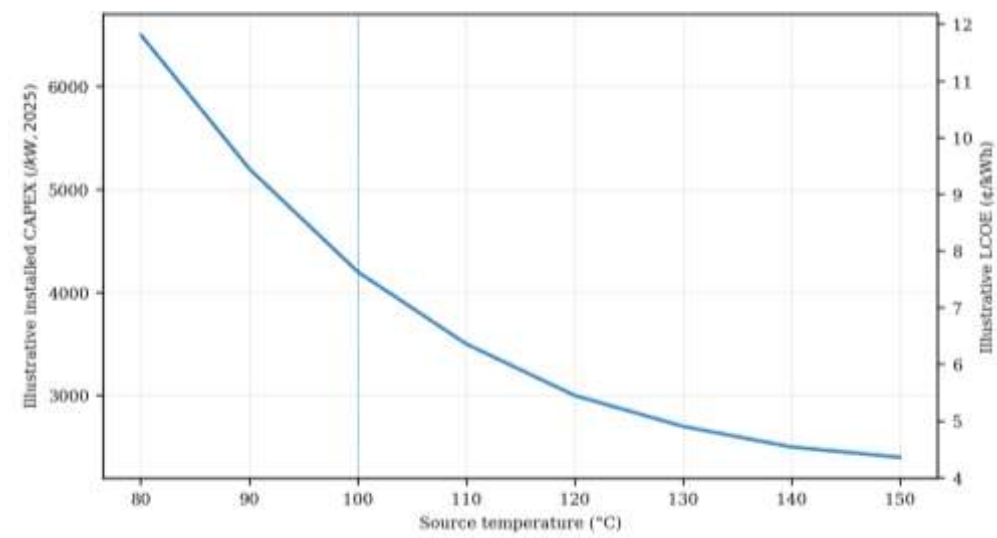


Table 2. Base Economic Parameters

Parameter	Base value	Interpretation
Discount rate	7% real	Base financing assumption
Project life	20 years	Economic life
Capacity factor	75%	Continuous industrial source with outages
Fixed O&M	2.5% of CAPEX/yr	Screening assumption
Avoided electricity value	8.62 ¢/kWh	2025 U.S. industrial average reference
Site realization before cost screen	65%	Non-price deployability factor
CAPEX at 80 °C	\$6,500/kW	Illustrative base curve
CAPEX at 120 °C	\$3,000/kW	Illustrative base curve
CAPEX at 150 °C	\$2,400/kW	Illustrative base curve

Uncertainty and Sensitivity Analysis

A 6,000-run Monte Carlo simulation propagates uncertainty in national low-grade allocation, sector-specific allocation, representative source temperature, capture fraction, net efficiency, installed cost, and avoided electricity value. Lognormal perturbations are used for strictly positive resource and cost multipliers, while source temperatures are normally perturbed and truncated to the study domain. Monte Carlo output is reported as 5th, 50th, and 95th percentiles. A separate one-at-a-time tornado analysis illustrates the directional influence of the principal technical assumptions.

FINDINGS, DATA ANALYSIS & PRESENTATION

National Low-Grade Resource Estimate

The base case produces 724 TBtu/yr of gross sub-150 °C waste heat from 15,742 TBtu/yr of manufacturing fuel consumption. Chemicals contribute 198.8 TBtu/yr, paper 160.2 TBtu/yr, petroleum and coal products 106.3 TBtu/yr, and food 92.6 TBtu/yr. These four sectors account for 77.1% of the modeled gross resource.

Table 3. Base-Case Technical Potential by Manufacturing Sector

Sector	Gross low-grade heat (TBtu)	Captured (TBtu)	heat	Net η	Generation (GWh/yr)	Technical MW
Chemicals	198.8	119.3		4.80%	1678	255.4
Paper	160.2	94.1		4.45%	1228	186.9
Petroleum & coal products	106.3	65.1		5.15%	983	149.6
Food	92.6	52.1		3.75%	573	87.2
Primary metals	26.1	16.3		5.50%	263	40.0
Nonmetallic mineral products	23.3	14.3		5.15%	216	32.8
Wood products	22.8	12.8		3.75%	141	21.4
Plastics & rubber	21.4	11.8		3.40%	117	17.9
Fabricated metal products	19.1	10.8		3.75%	118	18.0
Beverage & tobacco	17.2	9.5		3.40%	94	14.4
Transportation equipment	12.2	6.7		3.40%	67	10.1
Other manufacturing	5.9	3.2		3.05%	28	4.3
Machinery	5.7	3.1		3.40%	31	4.8
Computer & electronic products	4.5	2.4		2.70%	19	2.8
Electrical equipment	3.5	1.9		3.40%	19	2.9
Textile mills	3.4	2.0		4.10%	24	3.6
Textile product mills	1.1	0.6		3.40%	6	0.9

The national estimate is deliberately calibrated beneath DOE's 903 TBtu/yr broad low-temperature inventory. It should not be interpreted as an update or replacement for that DOE value. DOE's class extends to 230 °C, while the present modeled resource is restricted to representative sources below 150 °C and uses 2022 EIA sector fuel activity. The difference in years, boundaries, reference conditions, and methodology makes an exact reconciliation impossible without plant-level temperature distributions.

Figure 9: Base-Case Technical Waste-Heat-to-Power Capacity by Sector

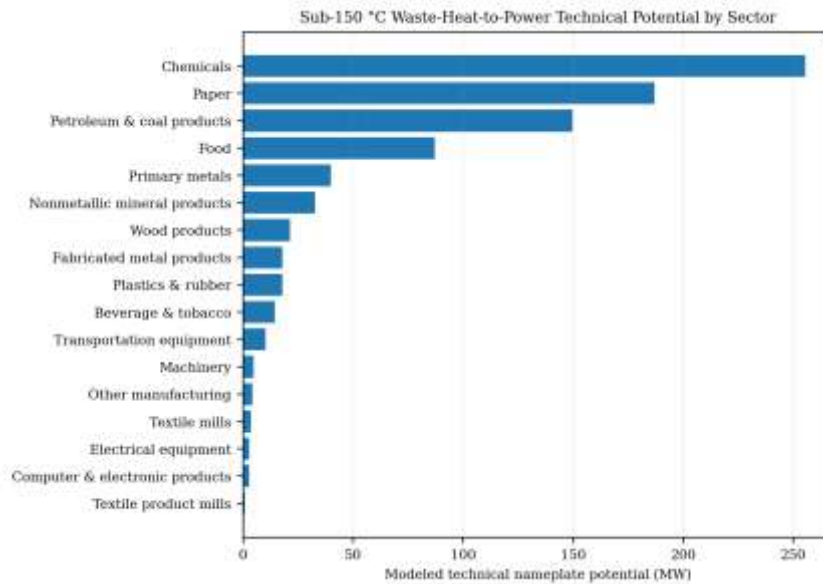
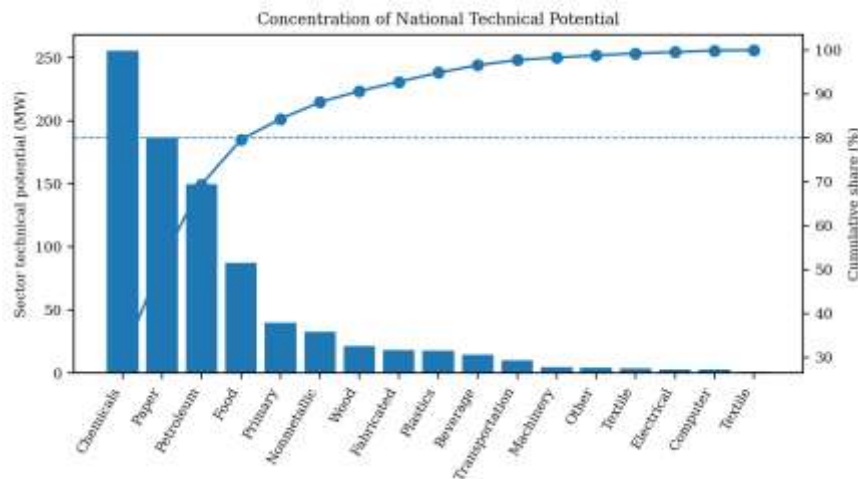


Figure 10: Pareto Concentration of National Technical Potential



Technical Electricity Potential

After applying temperature-dependent capture and net conversion assumptions, the base case produces 5.60 TWh/yr of net electricity, equivalent to 853 MW of nameplate capacity at a 75% capacity factor. Chemicals are the largest contributor at 255 MW, followed by paper at 187 MW, petroleum and coal products at 150 MW, and food at 87 MW. Together, the four sectors provide 79.6% of modeled technical capacity. The ranking differs somewhat from the gross heat ranking because source temperature changes both capture and net conversion efficiency.

Base-Case Economic Potential

The base economic screen yields approximately 494 MW of economic potential, corresponding to 3.25 TWh/yr of generation after the site-realization/economic factors are applied. This is approximately 58% of the 853 MW technical estimate. The result does not mean that 494 MW is currently construction-ready. It means that, under the stated cost, utilization, electricity-value, and site-realization

assumptions, that portion of the modeled resource lies on the favorable side of the screening curve. Chemicals, paper, and petroleum and coal products remain the largest economic opportunities because they combine large resource bases with representative temperatures above 110 °C in the model. Food retains a material resource but its representative 105 °C source produces a higher specific capital cost and higher levelized cost. Computer and electronic products are less attractive in the national screen because the assumed representative source temperature is 90 °C, where power-cycle output per unit thermal input is low and equipment cost per electric kilowatt is high.

Table 4. Base Economic Screening Results

Sector	Illustrative CAPEX (\$/kW)	LCOE (¢/kWh)	Technical MW	Economic MW
Chemicals	\$3,000	5.45	255.4	155.0
Paper	\$3,250	5.91	186.9	110.0
Petroleum & coal products	\$2,850	5.18	149.6	92.0
Food	\$3,850	7.00	87.2	45.0
Primary metals	\$2,700	4.91	40.0	24.9
Nonmetallic mineral products	\$2,850	5.18	32.8	20.2
Wood products	\$3,850	7.00	21.4	11.1
Fabricated metal products	\$3,850	7.00	18.0	9.3
Plastics & rubber	\$4,200	7.63	17.9	8.1
Beverage & tobacco	\$4,200	7.63	14.4	6.5
Transportation equipment	\$4,200	7.63	10.1	4.6
Machinery	\$4,200	7.63	4.8	2.2
Textile mills	\$3,500	6.36	3.6	2.0
Other manufacturing	\$4,700	8.54	4.3	1.5
Electrical equipment	\$4,200	7.63	2.9	1.3
Computer & electronic products	\$5,200	9.45	2.8	0.6
Textile product mills	\$4,200	7.63	0.9	0.4

Electricity-Price and Capital-Cost Sensitivity

Economic potential is highly sensitive to avoided electricity value. At very low industrial electricity values, even technically viable low-grade systems struggle to recover capital cost. As avoided value rises, the economic curve steepens because multiple sector/temperature groups cross the threshold within a relatively narrow price band. This behavior supports H3 and demonstrates why a single national average tariff should not be interpreted as a project-level conclusion.

Installed cost has a similarly strong effect. A 15–30% reduction in low-temperature installed cost—through improved expanders, modular heat exchangers, standardized balance-of-plant, better fouling control, or project replication—can move a large portion of the sector supply curve below the national electricity-value reference. Conversely, a 15–30% cost increase can sharply reduce screened economic capacity.

Figure 11: National Economic Potential versus Avoided Electricity Value

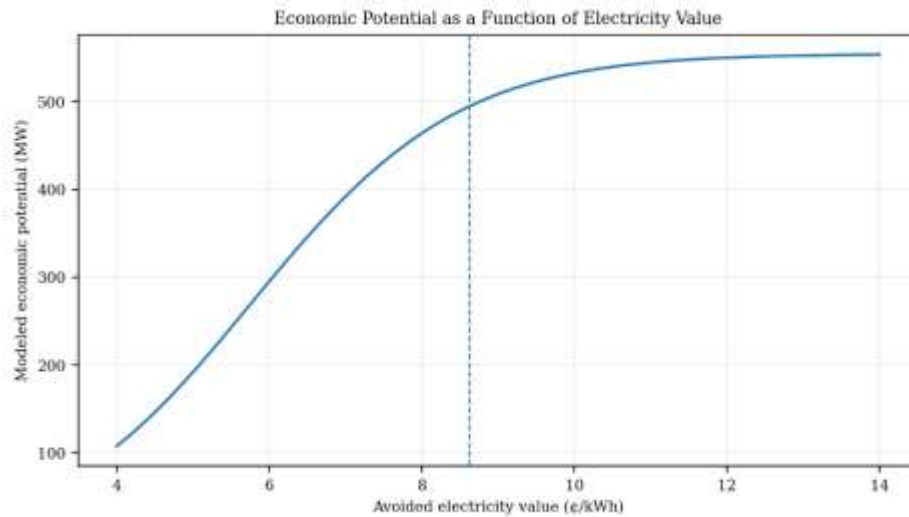
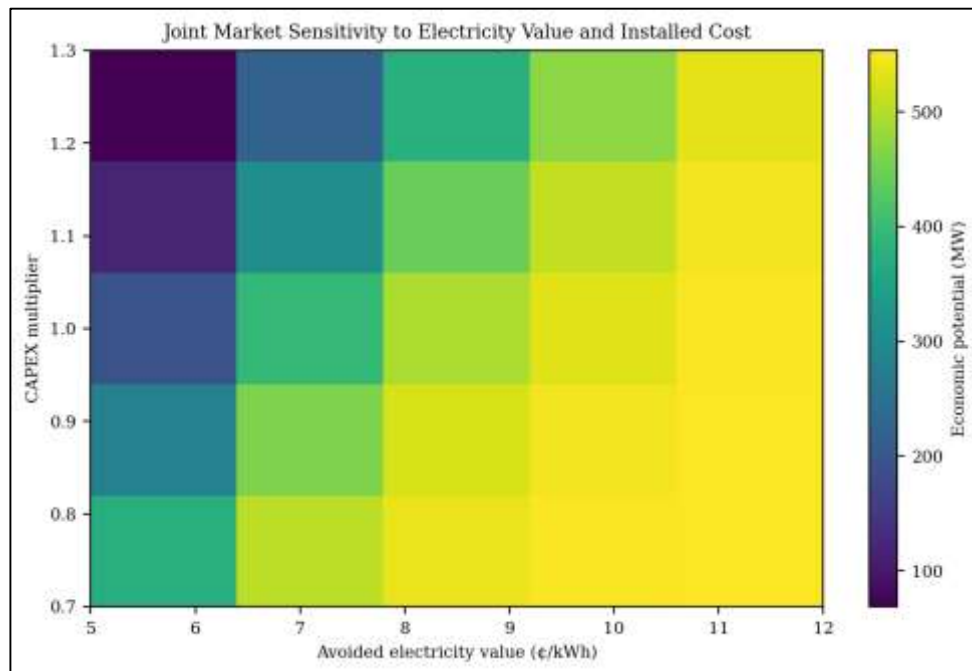


Figure 12: Joint Sensitivity of Economic Potential to Electricity Value and Installed Cost



Uncertainty Results

Monte Carlo propagation produces a technical potential range of approximately 579–1190 MW between the 5th and 95th percentiles, with a median of 836 MW. The corresponding economic range is approximately 262–693 MW, with a median of 465 MW. The gross sub-150 °C thermal resource has a 5th–95th percentile interval of approximately 565–917 TBtu/yr. The uncertainty range is intentionally broad because national low-grade allocation and source temperature are not directly measured in MECS. The result indicates that precision to the nearest megawatt would be misleading; the study

should be interpreted at the scale of hundreds of megawatts.

Figure 13: Monte Carlo Distribution of National Technical and Economic Potential

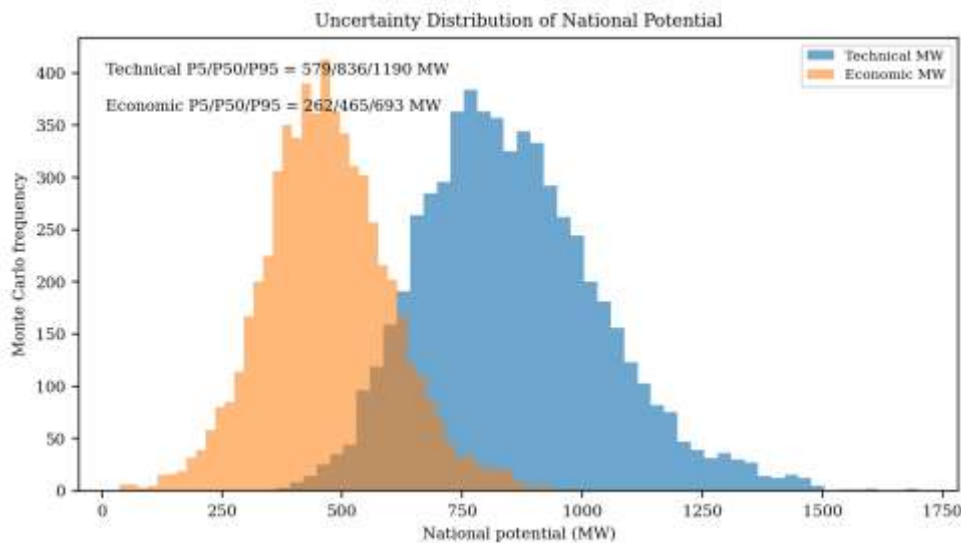
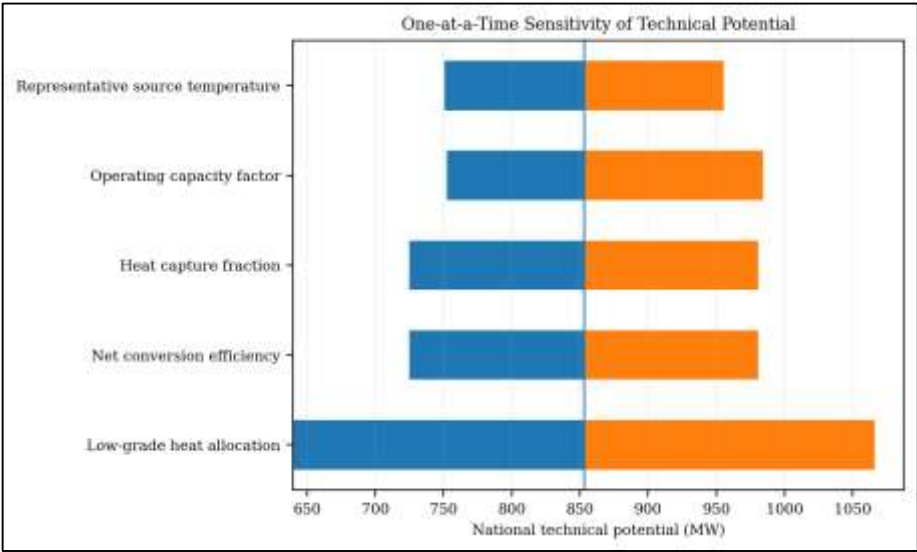


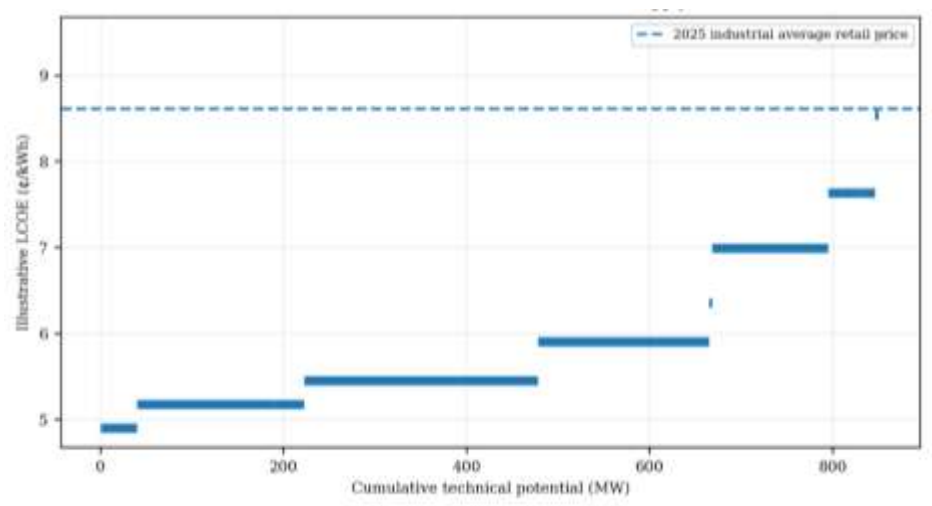
Figure 14: Sensitivity of National Technical Potential to Major Assumptions



National Cost Supply Curve

The sector cost supply curve places the warmer modeled sources – primary metals, petroleum and coal products, nonmetallic minerals, chemicals, and paper – toward the lower-cost portion of the national resource. The curve should not be read as a literal project merit order because each sector contains a broad distribution of site temperatures and project scales. Its value is analytical: it demonstrates that temperature heterogeneity changes the economic ordering of sectors and that resource magnitude alone is insufficient for prioritization.

Figure 15: Sector-Level National Cost Supply Curve for Sub-150 °C Waste-Heat Power



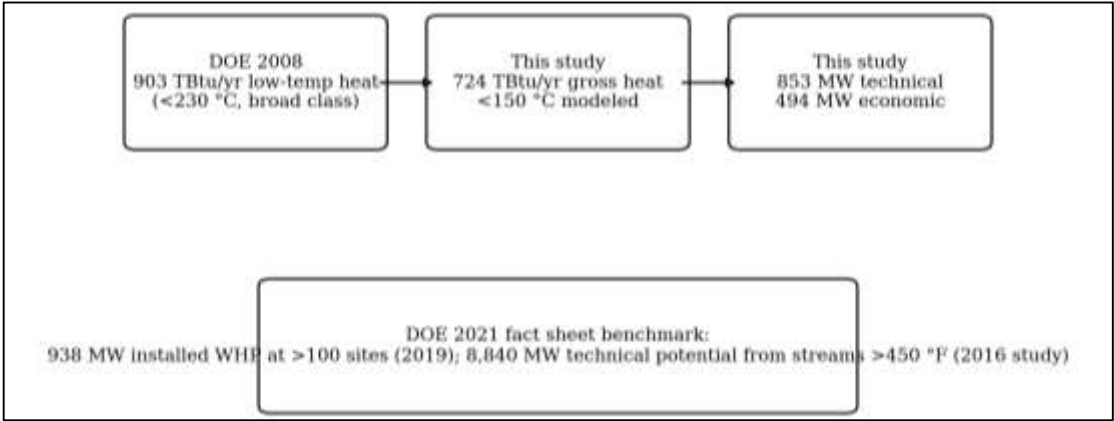
Potential Electricity Value and CO2 Displacement

At full technical generation, 5.60 TWh/yr valued at the 2025 national industrial average price corresponds to approximately \$483 million/yr of gross avoided electricity purchases before accounting for project-specific tariffs, demand charges, financing, taxes, incentives, or export restrictions. Using the 2024 U.S. average electric-sector CO2 output rate of 785 lb/MWh from U.S. EIA (2025), the same gross generation corresponds to approximately 2.00 million metric tons of potential annual CO2 displacement. This is an average-output calculation and should not be interpreted as marginal emissions analysis. The economic-potential generation would imply a proportionally smaller avoided-energy and emissions value.

Benchmark Comparison

The modeled 853 MW technical sub-150 °C potential is substantially below DOE’s 8,840 MW technical WHP benchmark for streams above 450 °F. This outcome supports H4 and is consistent with thermodynamics: lower-temperature heat has much lower work potential and higher equipment cost per electric kilowatt. At the same time, the low-grade estimate is comparable in order of magnitude to DOE’s reported 938 MW installed WHP baseline as of 2019, although the two quantities are not directly comparable because the installed fleet spans multiple heat-source types and temperatures. The comparison highlights the importance of temperature stratification in national policy. A headline statement that the United States has “several gigawatts of industrial WHP potential” can be true for high-temperature industrial streams while giving little information about sub-150 °C sources. Low-grade opportunities require their own technology, cost, and site-integration assumptions.

Figure 16: Scope-Consistent Comparison with DOE Waste-Heat and WHP Benchmarks



DISCUSSION

The model indicates that sub-150 °C heat can represent several hundred TBtu per year at the national scale even when it is only a few percent of manufacturing fuel input. This result is consistent with DOE's observation that low-temperature waste heat is large in quantity. However, thermal magnitude does not translate proportionally into electricity because only a fraction can be captured and low-temperature conversion efficiency is limited. The resulting technical electricity opportunity is therefore on the order of one gigawatt rather than tens of gigawatts in the base case.

The modeled results support H1. Chemicals, paper, petroleum and coal products, and food dominate the national technical opportunity. Their importance arises through different mechanisms: chemicals and petroleum have extremely large energy bases; paper combines large fuel use with substantial modeled low-grade thermal losses; food has a smaller energy base but a comparatively large low-temperature allocation. National research, demonstration, and equipment-standardization programs targeted at these sectors could therefore capture a large share of the screened opportunity.

The model supports H2 because technical and economic rankings are not identical. Lower-temperature sectors can contain substantial recoverable thermal energy but face lower net electrical efficiency and higher installed cost per kilowatt. The paper and chemical sectors perform strongly in both resource and economics under the base assumptions because their representative temperatures are high enough to reduce the low-grade penalty. The result reinforces the need for plant-level temperature-duration curves rather than annual energy totals alone.

The economic heatmap demonstrates that capital-cost reduction can create a large shift in economically screened capacity. This suggests that technology learning is not merely a project-level benefit; it changes the national potential curve. Modular ORC packages, lower-cost compact heat exchangers, improved expanders at small scale, integrated controls, lower working-fluid charge, standardized interconnection, and repeatable skid designs could therefore increase national economic potential even if thermodynamic efficiency changes only modestly.

A national WHP estimate should not imply that power generation is the preferred use of every warm stream. The exergy penalty of converting low-temperature heat to electricity is severe. Where a nearby process can use the heat directly, or where a heat pump can raise the temperature efficiently, direct thermal reuse may deliver more useful energy per unit of recovered heat. WHP is particularly attractive when thermal reuse is saturated, geographically unavailable within the plant, operationally mismatched, or strategically less valuable than electricity.

The DOE Industrial Decarbonization Roadmap emphasizes energy efficiency and cross-cutting thermal-system innovations (U.S. DOE, 2022). Sub-150 °C WHP fits this strategy as a residual-energy conversion option. Its strongest decarbonization role may be in continuously operating facilities where waste heat is already produced by an existing process and onsite electricity has a high avoided value. It can also complement electrification by reducing the net purchased-electricity requirement of industrial sites.

The grid value of WHP may change as electricity systems decarbonize. Average CO₂ displacement per MWh will tend to decline as zero-carbon generation expands, but electricity-price volatility, transmission constraints, resilience value, and behind-the-meter demand reduction can remain important. A forward-looking national potential model should therefore distinguish energy value from emissions value. The national results are consistent with the economic themes in ORC literature. [Tchanche et al. \(2011\)](#) and [Quoilin et al. \(2013\)](#) describe ORC as technically suitable for low-grade conversion but emphasize scale, fluid, and equipment constraints. [Vélez et al. \(2012\)](#) reports broad historical capital-cost ranges and notes that very small systems remained less mature. [Lecompte et al. \(2015\)](#) emphasizes that architecture improvements must be evaluated against additional complexity and cost. [Loni et al. \(2021\)](#) likewise concludes that waste-heat ORC can be attractive but is highly dependent on source and system design. The present national model converts those qualitative insights into an explicit temperature-cost sensitivity rather than assuming a single cost or efficiency for all sectors.

RECOMMENDATIONS

First, future federal data work should prioritize temperature-resolved waste-heat characterization. MECS already provides an excellent national energy-use foundation; a supplementary survey or

harmonized plant-assessment dataset describing waste-stream temperature bins, annual operating hours, medium, and available heat-capacity rate would substantially reduce uncertainty in national low-grade potential.

Second, sector-specific demonstration programs should emphasize chemicals, paper, petroleum/refining, and food processing because those sectors dominate the modeled national opportunity. Demonstrations should publish inlet/outlet temperature profiles, annual capacity factor, parasitic loads, installed cost, maintenance events, fouling performance, and net electricity output rather than only nameplate capacity.

Third, low-grade WHP technology development should focus on cost per net kilowatt rather than peak cycle efficiency alone. For sources near 80–110 °C, compact and fouling-tolerant heat exchangers, economical small expanders, standardized working-fluid management, simple controls, and reduced balance-of-plant may be more important to market penetration than marginal gains in ideal-cycle efficiency. Fourth, facility screening should use a thermal-use hierarchy. Direct process reuse, heat integration, heat pumping, cooling generation, thermal storage, and WHP should be compared using exergy, economics, operating compatibility, and site constraints. Electricity generation should be selected when it delivers the highest lifecycle value from the residual heat stream.

Fifth, national economic studies should avoid a single electricity-price assumption. U.S. industrial electricity prices vary substantially by state and tariff structure. Future work should connect MECS or plant-level thermal resources with geographic industrial-load data and state-level electricity prices to create a more realistic spatial economic-potential map.

Sixth, project-financing and policy analyses should distinguish technical from economic from deployable potential. Incentives, tax credits, clean-energy standards, interconnection rules, utility standby charges, and depreciation treatment can shift the economic screen without changing the underlying thermal resource.

LIMITATIONS

The largest limitation is that the sector low-grade waste-heat fractions are modeled assumptions rather than measured 2022 sector heat-stream inventories. Although the national result is calibrated against DOE's broader low-temperature benchmark and informed by DOE sector energy-loss context, the model cannot reveal the true temperature distribution inside each NAICS sector. Plant-level validation is therefore required before the results are used for investment decisions.

Second, each sector is represented by one characteristic source temperature. Actual plants contain many streams ranging from cooling water and condensate to exhaust and product heat. A temperature-duration distribution would be superior because both conversion efficiency and capital cost are nonlinear functions of source temperature.

Third, the economic model is a national screening model, not a detailed discounted-cash-flow project model. It excludes taxes, depreciation, incentives, debt/equity structure, demand-charge savings, escalation, curtailment, replacement costs, insurance, permitting, working capital, export compensation, and site-specific engineering. The CAPEX curve is an illustrative 2025-dollar scenario rather than a market quotation.

Fourth, the 65% site-realization factor is a simplifying parameter. Realization depends on stream cleanliness, fouling, space, ownership, heat-source continuity, process criticality, retrofit outage windows, environmental permits, hazard classification, working-fluid constraints, and interconnection requirements. These factors vary widely within sectors. Fifth, the emissions estimate uses an annual average grid-output CO₂ rate. Actual avoided emissions depend on the marginal generators displaced at the time and location of WHP output. Future regional modeling should use hourly marginal or nonbaseload factors where appropriate. Sixth, the study covers manufacturing-sector fuel consumption and does not attempt a full national assessment of non-manufacturing industrial sources such as oil and gas infrastructure, pipelines, data centers, wastewater facilities, mining, or nonmanufacturing CHP exhaust. Some of those sources are included in broader WHP databases and could materially increase national opportunity outside the defined scope.

CONCLUSION

This study develops a sector-level national methodology for estimating the technical and economic potential of electricity generation from industrial waste heat below 150 °C in the United States. The

central methodological contribution is boundary discipline: final 2022 EIA MECS fuel data are used as measured sector activity; DOE waste-heat, manufacturing-energy-loss, and WHP studies are used as external benchmarks; and the parameters required to translate energy use into low-grade thermal availability, capture, net electrical conversion, capital cost, and site realization are explicitly identified as modeling assumptions. Under the base case, the model estimates approximately 724 TBtu/yr of gross sub-150 °C waste heat, 5.60 TWh/yr of technical electricity, and 853 MW of technical nameplate capacity. A national economic screen at the 2025 average industrial electricity price yields approximately 494 MW, while uncertainty analysis places the 5th–95th percentile technical range at roughly 579–1190 MW. Chemicals, paper, petroleum and coal products, and food account for most of the modeled opportunity. The results are materially below DOE’s separate 8,840 MW high-temperature WHP technical-potential benchmark, as expected from the narrower and colder source domain. The findings suggest that sub-150 °C WHP is not a dominant national electricity resource but can represent a meaningful distributed industrial-efficiency opportunity measured in hundreds of megawatts to around one gigawatt. The priority for future research is therefore not to report a more precise national point estimate, but to improve temperature-resolved industrial data, validate sector allocation factors, develop lower-cost low-temperature conversion hardware, and connect national screening to plant-specific engineering and regional electricity economics.

REFERENCES

- [1]. Abdullah Mohammad, S. (2023). CUGAO₂ and CUINS₂ Quantum Dot Sensitization for Enhanced Photovoltaic Efficiency in Wearable Fiber-Shaped Solar Cells. *American Journal of Advanced Technology and Engineering Solutions*, 3(04), 209-261. <https://doi.org/10.63125/wysdvy71>
- [2]. Ashrafuzzaman, M. (2024). The impact of cloud-based management information systems on hrm efficiency: an analysis of small and medium-sized enterprises (SMES). *Academic Journal on Artificial Intelligence, Machine Learning, Data Science and Management Information Systems*, 1(01), 40-56. <https://doi.org/10.69593/ajaimldsmis.v1i01.124>
- [3]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(4), 108-137. <https://doi.org/10.63125/j0wk7j48>
- [4]. Debasish, A. (2022). Simulation-Based Thermal Management Framework for Reducing Energy Consumption in Advanced Manufacturing Systems. *International Journal of Scientific Interdisciplinary Research*, 1(01), 335-381. <https://doi.org/10.63125/6fcj7c89>
- [5]. Debasish, A. (2023). Thermal Behavior Modeling for Predicting Process Instability in Additive Manufacturing Systems. *International Journal of Scientific Interdisciplinary Research*, 4(4), 485-528. <https://doi.org/10.63125/b2nemb48>
- [6]. Debasish, A. (2024). AI-Based Quality Control Framework for Reducing Rework and Scrap in Additive Manufacturing Production. *Review of Applied Science and Technology*, 3(04), 402-447. <https://doi.org/10.63125/z29tv526>
- [7]. Debasish, A. (2025a). Design-for-Manufacturing Optimization for Improving Resilience in U.S. Additive Manufacturing Supply Chains. *American Journal of Interdisciplinary Studies*, 6(02), 185-204. <https://doi.org/10.63125/hxm3tb71>
- [8]. Debasish, A. (2025b). Physics-Informed Machine Learning for Predicting Thermal Distortion in Metal Additive Manufacturing. *American Journal of Scholarly Research and Innovation*, 4(01), 943-989. <https://doi.org/10.63125/ny974y17>
- [9]. Jannatul, F. (2025). Spinal Cord Injury and Neurorehabilitation Deep Learning-Based Prediction of Functional Recovery Trajectories After Traumatic Spinal Cord Injury. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 2865-2922. <https://doi.org/10.63125/m738bh82>
- [10]. Lecompte, S., Huisseune, H., van den Broek, M., Vanslambrouck, B., & De Paepe, M. (2015). Review of organic Rankine cycle (ORC) architectures for waste heat recovery. *Renewable and Sustainable Energy Reviews*, 47, 448-461. <https://doi.org/10.1016/j.rser.2015.03.089>
- [11]. Loni, R., Najafi, G., Bellos, E., Rajaei, F., Said, Z., & Mazlan, M. (2021). A review of industrial waste heat recovery system for power generation with Organic Rankine Cycle: Recent challenges and future outlook. *Journal of Cleaner Production*, 287, 125070. <https://doi.org/10.1016/j.jclepro.2020.125070>
- [12]. Md Anisur Rahman, M. (2024). State Income Tax Differentials and High-Skilled Labor Mobility in The United States: A Time Series Analysis. *American Journal of Interdisciplinary Studies*, 5(04), 222-267. <https://doi.org/10.63125/295bsn47>

- [13]. Md Anisur Rahman, M. (2025). The Role of AI-Enabled Business Intelligence in Financial Risk Assessment and Liquidity Monitoring. *Review of Applied Science and Technology*, 4(04), 195–246. <https://doi.org/10.63125/p4eezd93>
- [14]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use the Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, 4(01), 202-220. <https://doi.org/10.63125/pbjxp014>
- [15]. Md Ashfaq, S., & Abdullah Mohammad, S. (2022). CNT/PANI Composite Electrodes for Flexible Fiber-Shaped Dye-Sensitized Solar Cells: Synthesis, Characterization, and Photovoltaic Performance. *American Journal of Interdisciplinary Studies*, 3(02), 221-274. <https://doi.org/10.63125/m334mf41>
- [16]. Md Asif Ali Sheak, A., & Risha, A. (2022). The Role of IOT-Driven Energy Analytics in Improving Operational Efficiency and Sustainability in Modern Industrial Facilities. *American Journal of Interdisciplinary Studies*, 3(04), 807-841. <https://doi.org/10.63125/gm63q956>
- [17]. Md Kaium, H. (2023). A GIS-Based Multi-Criteria Decision-Support and Land-Suitability Optimization Framework for Climate-Resilient Urban and Regional Planning. *American Journal of Data Science and Analytics*, 4(06), 43–103. <https://doi.org/10.63125/wvq0sx87>
- [18]. Md Kaium, H. (2024). Machine Learning Enhanced GIS And AHP Modeling for High-Resolution Flood-Susceptibility Prediction, Vulnerability Assessment, and Risk Classification. *Review of Applied Science and Technology*, 3(02), 92–140. <https://doi.org/10.63125/fz8hv245>
- [19]. Md Kaium, H. (2025). Integrating Artificial Intelligence, Semantic Indoor Geospatial Modeling, And Network-Based Routing for High-Precision NG911 Emergency Location Intelligence. *International Journal of Scientific Interdisciplinary Research*, 6(1), 616–670. <https://doi.org/10.63125/5hc1xx56>
- [20]. Md Mahamud Pervaz, P. (2023). Integration of MES, SAP, And PI Historian Platforms for Real-Time Industrial Asset Performance Management. *Review of Applied Science and Technology*, 2(04), 393–445. <https://doi.org/10.63125/9ebtas97>
- [21]. Md Mahamud Pervaz, P. (2025). Development of a CMMS-Integrated Predictive Maintenance Framework for Industrial PLC and Drive Systems. *American Journal of Scholarly Research and Innovation*, 4(01), 894–942. <https://doi.org/10.63125/j33gtf31>
- [22]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70–102. <https://doi.org/10.63125/dyrpc387>
- [23]. Md. Rashedul, I., & Md Kaium, H. (2022). Development Of a Three-Dimensional Indoor Geospatial Network and Address Geocoding Framework for Next-Generation Emergency Dispatch and Response-Time Optimization. *Journal of Sustainable Development and Policy*, 1(02), 245–292. <https://doi.org/10.63125/tcw3mp48>
- [24]. Md. Shakhawat, H., & Md, F. (2024). Impact of Phishing Simulation Campaigns and Security Awareness Training on Human Risk Mitigation in Financial Institutions: A Quantitative Study. *American Journal of Data Science and Analytics*, 5(10), 48–85. <https://doi.org/10.63125/4j8h1484>
- [25]. Mohammad Abir Chowdhury, S. (2023). Role of AI-Assisted Risk Assessment in Enhancing Audit Planning Efficiency and Risk Prioritization in Public-Safety Organizations. *International Journal of Scientific Interdisciplinary Research*, 4(4), 529–576. <https://doi.org/10.63125/qd6nn437>
- [26]. Mohammad Abir Chowdhury, S. (2025). Application of Machine Learning and Anomaly-Detection Algorithms for Fraud Detection in U.S. Government Financial Operations. *American Journal of Interdisciplinary Studies*, 6(02), 139–184. <https://doi.org/10.63125/fkf19309>
- [27]. Mohammad Abir Chowdhury, S., & Tonay, P. (2022). An Empirical Analysis of the Impact of Robotic Process Automation and Continuous Auditing on the Timeliness And Accuracy Of Financial Reporting Assurance. *International Journal of Business and Economics Insights*, 2(4), 73–126. <https://doi.org/10.63125/7p8dcr47>
- [28]. Mohammad Badrul, A. (2025). SCADA And IOT-Enabled Smart Water Metering: A Systematic Review of Resilient Supply Monitoring. *International Journal of Scientific Interdisciplinary Research*, 6(1), 576–615. <https://doi.org/10.63125/at8pnx81>
- [29]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning-Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, 3(02), 33–77. <https://doi.org/10.63125/y3yfxa92>
- [30]. Mohammad Shoriful Hossan, S. (2022). A Performance-Based Framework for Arc-Flash Hazard Reduction and Electrical Reliability Improvement in Brownfield Industrial Distribution Systems. *Review of Applied Science and Technology*, 1(04), 447–463. <https://doi.org/10.63125/a70vj720>
- [31]. Mst Kaniz, F. (2022). Language Access and Health Equity: Role of Multilingual Administrative Staff in Reducing Healthcare Disparities Among South Asian Immigrant Communities in The U.S. *International Journal of Scientific Interdisciplinary Research*, 1(01), 274–315. <https://doi.org/10.63125/xqhss825>
- [32]. Nishat, J. (2023). Communicable Disease Prevention in a Post-Pandemic Era: A Global Review of Public Health Education, Surveillance, and Community-Level Interventions. *International Journal of Scientific Interdisciplinary Research*, 4(4), 630–678. <https://doi.org/10.63125/mnqefj36>

- [33]. Nishat, J. (2025). Leveraging Machine Learning to Identify and Address Maternal Health Disparities in Underserved U.S. Communities. *American Journal of Data Science and Analytics*, 6(12), 125-169. <https://doi.org/10.63125/c2t7r719>
- [34]. Nishat, J., & Jahanara, A. (2024). Machine Learning Approaches for Early Prediction of High-Risk Pregnancy in Underserved U.S. Populations. *American Journal of Interdisciplinary Studies*, 5(04), 268-309. <https://doi.org/10.63125/5gh5df13>
- [35]. Nishat, J., & Mst Kaniz, F. (2022). A Review of the Impact of Covid-19 On Maternal and Child Health Service Utilization in Bangladesh. *American Journal of Scholarly Research and Innovation*, 1(02), 223-269. <https://doi.org/10.63125/vgv5s742>
- [36]. Nuzhat Sadia, P. (2025). Integrating Business Intelligence Dashboards for Real-Time Supply Chain Visibility and Operational Decision Support. *American Journal of Data Science and Analytics*, 6(12), 170-216. <https://doi.org/10.63125/1es4f763>
- [37]. Quoilin, S., Van Den Broek, M., Declaye, S., Dewallef, P., & Lemort, V. (2013). Techno-economic survey of Organic Rankine Cycle (ORC) systems. *Renewable and Sustainable Energy Reviews*, 22, 168-186. <https://doi.org/10.1016/j.rser.2013.01.028>
- [38]. Sadia, Z. (2025). Predictive Analytics for Financial Performance Forecasting and Reporting Quality: Evidence from Data-Driven Financial Management Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 2795-2812. <https://doi.org/10.63125/zstqn346>
- [39]. Shaiful, M., Anisur, R., & Md, A. (2022). A Systematic Literature Review on the Role of Digital Health Twins in Preventive Healthcare For Personal and Corporate Wellbeing. *American Journal of Interdisciplinary Studies*, 3(04), 1-31. <https://doi.org/10.63125/negjw373>
- [40]. Tchanche, B. F., Lambrinos, G., Frangoudakis, A., & Papadakis, G. (2011). Low-grade heat conversion into power using organic Rankine cycles – A review of various applications. *Renewable and Sustainable Energy Reviews*, 15(8), 3963-3979. <https://doi.org/10.1016/j.rser.2011.07.024>
- [41]. Tonay, P. (2025). Machine Learning for Fraud Detection in Enterprise Financial Systems. *American Journal of Advanced Technology and Engineering Solutions*, 1(02), 304-318. <https://doi.org/10.63125/d0fhp873>
- [42]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial Intelligence-Based Decision Support Systems and Managerial Performance. *American Journal of Advanced Technology and Engineering Solutions*, 4(04), 154-184. <https://doi.org/10.63125/wmz8dc67>
- [43]. U.S. Department of Energy. (2008). Waste Heat Recovery: Technology and Opportunities in U.S. Industry. Industrial Technologies Program. https://www1.eere.energy.gov/manufacturing/intensiveprocesses/pdfs/waste_heat_recovery.pdf
- [44]. U.S. Department of Energy. (2021a). Manufacturing Energy and Carbon Footprints (2018 MECS). <https://www.energy.gov/cmei/ito/manufacturing-energy-and-carbon-footprints-2018-mecs>
- [45]. U.S. Department of Energy. (2021b). Combined Heat and Power Technology Fact Sheet Series: Waste Heat to Power. https://betterbuildingssolutioncenter.energy.gov/sites/default/files/attachments/Waste_Heat_to_Power_Fact_Sheet.pdf
- [46]. U.S. Department of Energy. (2022). Industrial Decarbonization Roadmap. <https://www.energy.gov/sites/default/files/2022-09/Industrial%20Decarbonization%20Roadmap.pdf>
- [47]. U.S. Energy Information Administration. (2025). United States Electricity Profile 2024. <https://www.eia.gov/electricity/state/unitedstates/>
- [48]. U.S. Energy Information Administration. (2026a). Manufacturing Energy Consumption Survey: Final results from the 2022 MECS. <https://www.eia.gov/consumption/manufacturing/>
- [49]. U.S. Energy Information Administration. (2026b). 2022 Manufacturing Energy Consumption Survey data. <https://www.eia.gov/consumption/manufacturing/data/2022/>
- [50]. U.S. Energy Information Administration. (2026c). Prices and factors affecting prices: Electricity prices by customer type. <https://www.eia.gov/energyexplained/electricity/prices-and-factors-affecting-prices.php>
- [51]. U.S. Environmental Protection Agency. (2025). eGRID 2023 summary data. <https://www.epa.gov/egrid/summary-data>
- [52]. Uddin, H. M. M., & Risha, A. (2024). Hybrid Cloud Security and Compliance in U.S. Enterprises: Addressing Data Privacy Risks and Governance Challenges. *American Journal of Scholarly Research and Innovation*, 3(01), 153-197. <https://doi.org/10.63125/qcy0cj46>
- [53]. Vélez, F., Segovia, J. J., Martín, M. C., Antolín, G., Chejne, F., & Quijano, A. (2012). A technical, economical and market review of organic Rankine cycles for the conversion of low-grade heat for power generation. *Renewable and Sustainable Energy Reviews*, 16(6), 4175-4189. <https://doi.org/10.1016/j.rser.2012.03.022>