

Thermofluid Analysis and Biostatistical Modelling of Thermal Exposure Among Workers in Gas-Fired Power Plants

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ABSTRACT

Thermal exposure in gas-fired power plants is shaped by combustion-related heat release, hot equipment surfaces, radiation, ventilation, humidity, workload, clothing, and the duration of task exposure, making a single ambient temperature measurement insufficient for evaluating worker heat strain. This study presents a scenario-based thermofluid and biostatistical modelling framework for quantifying thermal exposure in representative gas-fired combined-cycle power plant work zones. The thermofluid component uses steady energy balances, convective heat transfer, radiative exchange, humidity effects, wet-bulb globe temperature (WBGT), metabolic heat production, and clothing adjustment to characterise worker-facing thermal conditions. A synthetic worker-shift dataset of 300 observations was generated from the modelled exposure ranges to demonstrate logistic regression for heat-strain probability. Three learning-outcome objectives were specified: to quantify zone-level thermal exposure; to estimate the association between thermal-workload variables plus modelled heat strain; to evaluate predictive behaviour across exposure scenarios. Modelled mean WBGT ranged from 28.9 °C in the control room to 34.9 °C around the heat-recovery steam generator (HRSG), while the HRSG zone produced the highest modelled maximum of 37.9 °C. In the synthetic demonstration dataset, each 1 °C increase in WBGT was associated with 38.4% higher odds of modelled heat strain (OR 1.384, 95% CI 1.234–1.552, $p < .001$). Metabolic rate also showed a positive association (OR 1.006 per W, $p = .022$). The findings demonstrate how thermofluid outputs can be translated into worker-level risk estimates, while emphasising that the statistical results are illustrative until validated against measured occupational data.

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INTRODUCTION

Gas-fired power plants contain several work environments in which workers can experience thermal loads that differ substantially over short distances and across operating states. Combustion chambers, gas turbines, exhaust systems, heat-recovery steam generators, steam piping, valves, pumps, auxiliary skids, and enclosed plant rooms can release or retain heat through convection, radiation, conduction, or combinations of these mechanisms. The resulting exposure is not determined by air temperature alone because humidity, air movement, radiant temperature, metabolic heat production, clothing, task duration, and recovery periods influence the thermal burden experienced by a worker. Recent occupational heat research has therefore increasingly favoured exposure measures that connect environmental conditions to physiological or work-related outcomes rather than treating temperature as an isolated hazard indicator (Cheveldayoff *et al.*, 2023).

The occupational significance of this problem has increased as extreme heat becomes more frequent in many regions, particularly where industrial work is performed in warm climates or where high internal heat loads add to outdoor meteorological conditions. Dasgupta *et al.* (2024) observed that heat stress affects health, the ability to work, the supply of labour and production. The extent of exposure to intense heat at work varies greatly different economies as Nigeria experiences among of the highest rates of heat-exposed

working hours (Li *et al.*, 2025). The results are relevant for power generation since plant workers may be particularly vital during times when equipment is hot, the air is warm and the labour is hard.

There is also evidence that only exists when the power is made. Chaiprakarn *et al.* (2024) utilised WBGT to define heat stress in several industrial processes and studied the level of heat exposure for workers in 23 distinct sections of a power plant. Their study suggests that rather than having one grade for the whole facility for everyone, evaluations should be more tailored to regions. Another study of power plant workers in a hot area showed that individual characteristics and work-related factors exacerbated heat-related results (Dehdashti *et al.*, 2025) and that environmental exposure should be assessed along with worker and task variables.

The WBGT approach is still useful as it looks at the effects of air temperature, humidity, air movement and direct heat utilising dry-bulb temperature, natural wet-bulb temperature and globe temperature. Abbasi *et al.* (2023) compared 18 empirical heat-stress indices to physiological data and found WBGT to be the most accurate of the group. Bernard *et al.* (2023) studied time-weighted WBGT methods in more detail and showed that exposure averaging, rather than a single instantaneous reading, is the preferable way to signal varying levels of exposure during a work shift. This is also important to remember in power plants because staff go from control rooms to turbine halls, outdoor equipment areas, repair

workshops and high radiation sites during the course of a shift. Another engineering perspective is the thermofluid analysis, because it may determine the physical processes that cause the temperature environment to which workers are exposed. Fluid flow, turbulence, heat transfer, component temperatures and changing behaviour are all often studied at in gas-turbine heat-transfer models. Yang et al. (2024) pointed out that computational fluid dynamics is helpful for determining local temperature fields when experiments are difficult to undertake. The necessity of investigating heat performance in gas-turbine power plants and the Utility of computer tools to evaluate the mechanics is additionally highlighted by Surase et al. (2024). A research focusing on workers can link plant thermodynamics to the exposure at work by transforming equipment heat release, air temperature, humidity, radiation and ventilation to WBGT or comparable exposure data. Physiological research informs us that exposure to warmth is related with a measurable strain. Ioannou et al. (2022) studied outdoor workers and found significant relationships between WBGT and changes in core temperature, skin temperature, heart rate, urine specific gravity and metabolic rate. Meng et al. (2022) also showed relationships between WBGT, physiological responses and subjective heat in the workplace of acclimatised persons. More recent work has focused on predictive techniques. For instance, Ojha et al. (2024) demonstrated that an ensemble learning based worker-centered heat-strain framework, which relies on physiological inputs, could predict heat strain with an accuracy greater than 93%. These developments indicate that occupational heat assessment can benefit from combining engineering exposure variables with statistical prediction rather than treating environmental measurements as descriptive values alone.

Despite these advances, an important methodological gap remains in the integration of plant-level thermofluid behaviour, worker exposure indices, and biostatistical risk modelling within a single framework tailored to gas-fired power generation. Existing power-plant studies provide evidence of occupational heat exposure, while engineering studies describe thermal performance of gas turbines and associated equipment, but the two streams are rarely connected to a statistical model that estimates worker-level heat-strain probability. The present study addresses that gap through a reproducible scenario-based framework that can later be populated with field measurements from a real gas-fired plant.

MATERIALS AND METHODS

Study Design

A scenario-based computational study was designed to integrate thermofluid heat-transfer analysis with biostatistical modelling. Four representative work zones were considered: the control room, turbine hall, gas skid area, and HRSG area. The selected zones represent progressively greater combinations of internal heat generation, hot surface exposure, radiant exchange, and worker task demand. The analysis was designed for a gas-fired combined-cycle power plant because the technology contains a gas turbine, combustion system, heat-recovery steam generator, steam cycle, auxiliary equipment, and control facilities that create distinct thermal environments.

No human participants were recruited for this manuscript, no identifiable worker information was used, and no clinical measurements were collected. The worker-level dataset described below is synthetic and was created solely to demonstrate the statistical workflow. Consequently, the reported odds ratios and predicted probabilities are not

estimates of risk in a named power plant population. If the framework is implemented as a field study, ethical approval, informed consent, occupational monitoring procedures, calibration records, and data-governance arrangements should be completed before worker measurements are collected.

Thermofluid Formulation

The thermal environment was represented using a steady-state energy balance for each work zone. The general balance was expressed as

$$\dot{Q}_{in} - \dot{Q}_{out} = 0 \quad (1)$$

where $\dot{Q}_{in}$ represented heat entering the zone through equipment surfaces, hot process streams, solar or ambient sources where applicable, and internal loads, while $\dot{Q}_{out}$ represented heat removed through ventilation, forced air movement, conduction, and other defined pathways. For equipment surfaces, the convective heat-transfer rate was represented as

$$\dot{Q}_{conv} = h_A(T_s - T_a) \quad (2)$$

where h is the convective heat-transfer coefficient, A is the exposed surface area, T_s is the surface temperature, and T_a is the local air temperature.

Radiant exchange was represented through the Stefan–Boltzmann relationship

$$\dot{Q}_{rad} = \varepsilon \sigma A(T_s^4 - T_{sur}^4) \quad (3)$$

where ε is surface emissivity, σ is the Stefan–Boltzmann constant, and T_{sur}^4 is the effective surrounding radiant temperature.

This term is important around turbines, exhaust systems, hot piping, HRSG surfaces, and uninsulated valves because a worker can receive substantial radiant heat even when local air temperature is lower than the temperature of the equipment surface. The combined sensible heat contribution from convection and radiation was used to construct a representative globe-temperature response for each zone.

Ventilation was represented using the sensible heat-removal relationship

$$\dot{Q}_{vent} = \rho \dot{V} c_p (T_a - T_{supply}) \quad (4)$$

where ρ is air density, $\dot{V}$ is volumetric airflow rate, c_p is the specific heat capacity of air, and T_{supply} is the incoming-air temperature.

Moisture conditions were incorporated through relative humidity and natural wet-bulb temperature because evaporative cooling is strongly influenced by ambient vapour pressure. The thermofluid model therefore treats ventilation as both an engineering control and a determinant of worker thermal exposure.

Thermal Exposure INDEX

Indoor WBGT was calculated using

$$WBGT = 0.7T_{nwb} + 0.3T_g \quad (5)$$

where T_{nwb} is natural wet-bulb temperature and T_g is globe temperature.

This form is appropriate for indoor locations or outdoor locations without direct solar radiation; where direct solar exposure is present, the outdoor form would include the dry-bulb temperature contribution. As WBGT is commonly used in assessing heat in the workplace and has shown useful connections with bodily heat-strain measures (Abbasi et al., 2023) it was chosen.

As part of the exposure assessment, metabolic rate and clothing were also taken into account. This is because workers can have different physiological responses to the same working conditions if they do different tasks or wear

different protective clothing. The time-weighted approach was

$$WBGT_{TW} = \frac{\sum (WBGT_i \times t_i)}{\sum t_i} \quad (6),$$

where $WBGT_{TW}$ = time-weighted average WBGT over the work shift ($^{\circ}\text{C}$), $WBGT_i$ = WBGT value during exposure segment i ($^{\circ}\text{C}$), t_i = duration of exposure segment i (h or min), n = total number of exposure segments during the work shift and $\sum$ = summation over all exposure segments. Bernard et al. (2023) showed why time-weighted approaches are relevant when workers experience heterogeneous conditions during a shift. This study therefore distinguishes zone-level peak exposure from the time-weighted shift exposure that would be more relevant for cumulative assessment.

Scenario Inputs

Representative input ranges were defined to demonstrate the interaction between environmental and occupational variables. The scenarios used dry-bulb air temperatures centred around 31°C before zone-specific thermal adjustments, relative humidity centred around 62%, globe temperature above dry-bulb temperature because of radiant heat, metabolic rates centred around 250 W, and clothing insulation centred around 0.6 clo. Zone-specific heat additions were applied to represent differences in equipment heat load. These values are modelling assumptions rather than measurements from a named facility.

Table 1: Modelled WBGT Exposure Across Representative Gas-Fired Power Plant Work Zones

Zone	Modelled mean WBGT ($^{\circ}\text{C}$)	Modelled maximum WBGT ($^{\circ}\text{C}$)	Relative thermal exposure
Control room	28.9	32.4	Lower
Gas skid	33.1	36.4	High
Turbine hall	33.8	38.4	High
HRSO area	34.9	37.9	Highest

The scenario ranges were chosen to overlap occupational heat conditions reported in recent industrial research rather than to imply that every gas-fired plant will experience these values. Chaiprakarn et al. (2024) found meaningful spatial differences in power-plant heat exposure, while recent work on industrial workers confirms that WBGT can vary substantially across tasks and environmental conditions (Meng et al., 2022).

Synthetic Worker-Shift Dataset

A synthetic dataset containing 300 worker-shift observations was generated from the thermofluid scenario distributions. Each observation contained work zone, dry-bulb temperature, relative humidity, globe temperature, natural wet-bulb temperature, WBGT, metabolic rate, clothing insulation, and a binary modelled heat-strain outcome. The binary outcome was generated from a logistic probability function so that the statistical demonstration preserved a plausible monotonic relationship between increasing WBGT, increasing workload, and increasing heat-strain probability. The dataset was not intended to reproduce the prevalence of heat strain in any real worker population.

The use of synthetic observations permits the complete statistical workflow to be demonstrated without fabricating field measurements. This distinction is essential because a statistical coefficient derived from generated observations cannot be interpreted as an empirical occupational epidemiological finding. The approach instead illustrates how a future field dataset could be analysed after environmental sensors, physiological measures, work-rest records, and validated heat-strain outcomes have been collected.

Biostatistical Analysis

Binary logistic regression was selected because the demonstration outcome was coded as 0 for no modelled heat strain and 1 for modelled heat strain. The general model was $\text{logit}(P) = \beta_0 + \beta_1 WBGT + \beta_2 M + \beta_3 Clo + \beta_4 RH$, (7) where P is the probability of heat strain, M is metabolic rate, Clo is clothing insulation, and RH is relative humidity. Exponentiated coefficients were interpreted as odds ratios. For WBGT, the odds ratio represents the multiplicative change in the odds of modelled heat strain for each 1°C increase in WBGT, holding the other variables constant.

Two-sided tests used $\alpha = .05$, and 95% confidence intervals were calculated from the estimated standard errors. Model discrimination was considered through the fitted probabilities and pseudo- R^2 rather than treating statistical significance as proof of clinical or occupational importance. This distinction is important because even a statistically strong association may have limited operational value if exposure ranges are narrow, if measurement error is substantial, or if the model does not generalise to a different plant.

Model Quality, Sensitivity, and Reproducibility

Sensitivity analysis was structured around changes in WBGT, metabolic rate, relative humidity, clothing insulation, and work-rest exposure. The principal engineering sensitivity was expected to arise from radiant temperature and ventilation because these variables directly alter globe temperature and air temperature. The statistical sensitivity was evaluated by examining predicted heat-strain probability over a WBGT range of $25\text{--}38^{\circ}\text{C}$ while holding metabolic rate, clothing, and humidity at representative values. This approach provides a transparent link between engineering exposure changes and predicted worker risk.

For a field implementation, temperature and humidity sensors should be calibrated against traceable standards, globe thermometers should be positioned to represent worker exposure rather than equipment surfaces alone, airflow should be recorded where ventilation is an important control, and task-level metabolic rates should be estimated from an accepted occupational workload framework. The data collection plan should also record work-rest cycles because a peak WBGT lasting only a few minutes has a different interpretation from a sustained exposure across several hours.

RESULTS AND DISCUSSION

Thermofluid Exposure Distribution

The model produced clear spatial differences in worker-facing thermal exposure, with the control room presenting the lowest mean WBGT and the HRSO area presenting the highest mean value. The control-room mean of 28.9°C reflects a comparatively low internal heat load and stronger potential for mechanical cooling, whereas the HRSO mean of 34.9°C represents the combined effect of hot process equipment, elevated radiant temperature, and reduced

capacity for immediate heat removal. The turbine hall also produced a high thermal burden, with a modelled mean WBGT of 33.8 °C and a maximum of 38.4 °C.

The spatial pattern is compatible with the actual layout of a combined-cycle plant as the HRSG and turbine systems feature high temperature process streams and huge equipment surfaces that can exchange heat with the environment. Thermal exchange between the working gas and metal components might influence the behaviour of the system, therefore, Yang et al. (2024) defined heat transfer as an important feature of gas-turbine transient modelling. From an occupational perspective, those same thermal interactions can create local heat sources that remain relevant after the primary process heat has been converted into mechanical or electrical output.

The gas skid produced a mean WBGT of 33.1 °C and a maximum of 36.4 °C, indicating that auxiliary areas should not automatically be classified as low-risk simply because

they are separated from the main turbine enclosure. The exposure can arise from hot pipework, valves, compressors, enclosed geometry, restricted airflow, and maintenance tasks that require workers to remain close to equipment. Chaiprakarn et al. (2024) similarly demonstrated the importance of assessing multiple operating locations within a power plant rather than assigning one heat-stress value to the entire facility.

The control-room result requires careful interpretation because a mean WBGT of 28.9 °C does not mean that heat risk is absent. Short-duration exposure during plant rounds, equipment checks, emergency response, or transition between conditioned and unconditioned spaces may produce higher instantaneous exposure than the room average suggests. Bernard et al. (2023) noted that time-weighted approaches are useful when exposures vary across a work period, which supports reporting both peak values and shift-level averages.

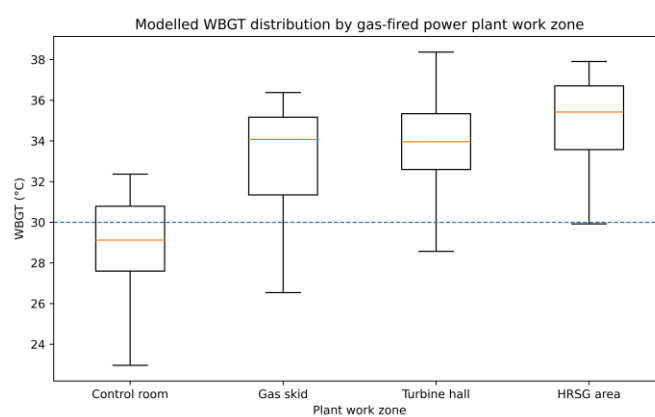


Figure 1: Modelled WBGT Distribution Across Representative Gas-Fired Power Plant Work Zones. The Dashed Line Marks 30°C as a Visual Reference for Scenario Comparison; it is not Presented as a Universal Exposure Limit. Chaiprakarn et al. (2024) and Abbasi et al. (2023)

Biostatistical Model

In the synthetic worker-shift dataset, 74 of 300 observations were assigned a modelled heat-strain outcome, giving an illustrative event proportion of 24.7%. The HRSG area had the highest event proportion at 44.4%, followed by the turbine

hall at 24.7%, the gas skid at 23.8%, and the control room at 7.5%. These values are generated outcomes and therefore describe the behaviour of the demonstration dataset rather than a measured prevalence among power-plant workers.

Table 2: Multivariable Logistic Regression Analysis of Modelled Heat Strain

Predictor	Coefficient (β)	Odds ratio	95% CI for OR	p-value
WBGT, per 1 °C	0.325	1.384	1.234–1.552	<.001
Metabolic rate, per W	0.006	1.006	1.001–1.011	.022
Clothing, per clo	0.154	1.167	0.113–12.079	.897
Relative humidity, per 1%	0.021	1.021	0.996–1.047	.104

The modelled WBGT coefficient was positive and statistically significant, with an odds ratio of 1.384 per 1 °C increase. Within the synthetic data-generating structure, this means that a 1 °C increase in WBGT corresponded to approximately 38% higher odds of the modelled heat-strain outcome after adjustment for metabolic rate, clothing insulation, and relative humidity. The relationship is directionally consistent with the physiological literature, where increasing WBGT has been associated with higher core temperature, skin temperature, and heart rate (Ioannou et al., 2022).

Metabolic rate was also positively associated with the modelled outcome, although its unit-scale odds ratio was

close to 1 because the predictor was measured in watts. Interpreted over a 50 W increase, the corresponding multiplicative change in odds is approximately $\exp(0.00597 \times 50)$, or 1.35. This illustrates why workload should be considered in addition to environmental exposure. Workers performing inspection or monitoring duties may have a different physiological response from maintenance personnel performing physically demanding tasks in the same thermal environment.

Clothing insulation was not statistically significant in this demonstration, and its confidence interval was wide, reflecting the limited independent information generated for this variable. This should not be interpreted as evidence that

clothing is unimportant. Cheveldayoff et al. (2023) identified occupational clothing as one of the factors that influence heat-related illness, and future field datasets should measure clothing ensembles more precisely, particularly where flame-resistant clothing, coveralls, gloves, helmets, or respiratory protection are required.

Relative humidity showed a positive coefficient but did not reach conventional statistical significance in the synthetic model. Humidity remains physically important because it limits evaporative cooling, particularly when air temperature is high. The absence of statistical significance in this demonstration is therefore more appropriately interpreted as a property of the synthetic dataset than as evidence against humidity as a determinant of thermal strain. A field study should collect continuous humidity data and examine

interactions between humidity, air temperature, and air movement rather than relying on a main-effect coefficient alone.

Predicted Heat-Strain Probability

The curve of predicted probabilities showed a gradual increase along the range of WBGT values, illustrating the capacity of the statistical model to transform an engineering exposure variable into risk estimates. Under typical conditions of workload, clothing and humidity, the estimated chance increased with WBGT from the mid-20s to the upper-30s °C. This is consistent with recent studies showing that occupational heat strain is more likely to occur under higher environmental heat load and exertion (Abbasi et al., 2023).

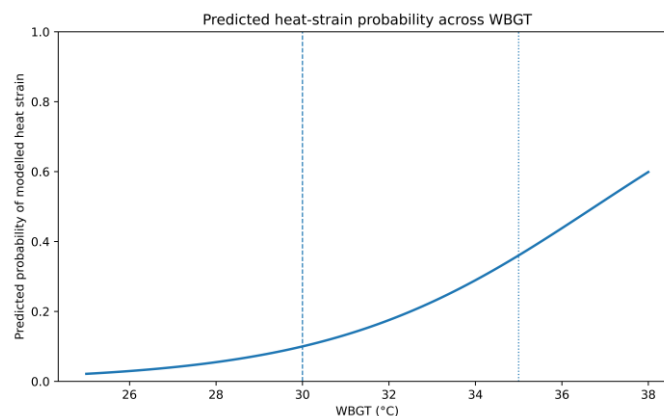


Figure 2: Predicted Probability of Modelled Heat Strain Across WBGT Values for Representative Metabolic Rate, Clothing Insulation, and Relative Humidity. The vertical Reference Lines are Scenario Markers Rather Than Universal Occupational Limits. Ioannou et al. (2022) and Abbasi et al. (2023)

The modelled probability curve also illustrates why a binary safe/unsafe classification can be inadequate for operational decision-making. Risk changes progressively rather than switching from zero to one at a single temperature. Hess et al. (2025) examined occupational heat-alert limit curves and showed that work-rest recommendations should be evaluated against the physiological objective of maintaining thermal equilibrium and limiting core temperature rise. A practical power-plant system can therefore use exposure bands to trigger progressively stronger controls, rather than waiting for a worker to develop symptoms.

Comparison with Recent Evidence

The modelled spatial pattern is compatible with recent power-plant evidence, although direct numerical comparison should be avoided because the present values are synthetic. Chaiprakarn et al. (2024) measured heat exposure across multiple operating locations and demonstrated the value of WBGT-based assessment in power generation. The present framework extends that approach by introducing a thermofluid explanation for why zones differ, followed by a statistical layer that converts exposure into a probability estimate.

The results also make sense from the assumptions driving research on industrial workers. Meng and colleagues (2022) examined how workers' bodies and minds that have become accustomed to heat respond to heat stress. Their results support the notion that environmental experience can explain how workers react. Ioannou et al. (2022) reported statistically significant associations between WBGT and a number of

biochemical markers in outdoor workers. The current framework therefore uses WBGT as a bridge between engineering heat transfer and worker-centred outcomes.

Recent predictive research provides further support for combining environmental measurements with worker-level information. Ojha et al. (2024) developed a physiological sensing framework that achieved high heat-strain classification accuracy using ensemble learning and domain adaptation. The present approach is deliberately simpler because logistic regression offers coefficients that plant engineers, occupational hygienists, and safety managers can interpret directly. More complex machine-learning models could be added after a sufficiently large field dataset becomes available, but the additional complexity should be justified by demonstrable improvement in prediction or decision support. The wider occupational evidence indicates that heat exposure has consequences beyond acute discomfort. Han et al. (2024) reported substantial productivity loss among construction workers exposed to elevated temperatures, particularly when WBGT exceeded higher exposure levels. Dasgupta et al. (2024) similarly described impacts on labour capacity and productivity at population level. In power generation, productivity should not be interpreted solely as output because heat-related fatigue, slower movement, reduced concentration, impaired judgement, and additional recovery breaks can influence maintenance quality and operational safety.

The relevance to Nigeria is particularly important because Li et al. (2025) estimated a high number of heat-exposed working hours in Nigeria within their global assessment. A

gas-fired power plant operating in a warm, humid climate can therefore experience a combined burden from external weather and internally generated equipment heat. The engineering response should include ventilation design, insulation of hot surfaces, radiant barriers, local cooling, maintenance planning, shaded recovery areas, and work-rest arrangements rather than relying on personal hydration alone.

Engineering Interpretation

From a thermofluid perspective, the highest-value interventions are those that reduce the heat entering the worker microenvironment before it reaches the worker. Improving insulation around hot equipment reduces radiative and convective heat transfer to the surrounding space, while increasing effective ventilation can remove sensible heat from occupied areas. Where process requirements prevent large changes in bulk ventilation, local exhaust or directed airflow may reduce the thermal load at the worker location. The relative contribution of each measure should be tested through the energy balance rather than selected solely on the basis of general practice.

Radiation deserves particular attention because a worker standing close to a hot surface can receive a substantial heat load even when air temperature appears acceptable. The fourth-power temperature relationship in the radiative heat-transfer equation means that high surface temperatures can produce disproportionately large radiant exchange. Consequently, equipment insulation, reflective shielding, increased separation distance, and redesign of frequently occupied maintenance positions may provide greater benefit than small reductions in room air temperature.

Ventilation effectiveness should also be evaluated at worker level. A high air-change rate does not necessarily provide adequate cooling if supply air bypasses the occupied zone or if hot air stratifies near the worker. CFD or reduced-order thermofluid models can identify stagnant regions, thermal plumes, recirculation zones, and heat accumulation around equipment. Yang et al. (2024) highlighted the role of numerical approaches in resolving heat-transfer behaviour in gas-turbine systems, while Surase et al. (2024) reviewed computational methods for thermal performance analysis in gas-turbine power plants.

Work-rest scheduling provides a second layer of control when engineering measures cannot reduce exposure sufficiently. The statistical model shows why a worker performing high-metabolic-rate maintenance in a high-WBGT zone can have substantially greater risk than a worker conducting low-intensity monitoring under the same ambient conditions. Hess et al. (2025) demonstrated the importance of examining work-rest recommendations against actual physiological responses, supporting the use of exposure-specific rather than generic rest periods.

Operational Implications

A practical plant heat-management programme should begin with a thermal map of the facility, using repeated WBGT measurements across representative operating states and task locations. The map should identify normal operating conditions, peak-load conditions, maintenance states, start-up, shutdown, and emergency scenarios because equipment heat release and ventilation patterns can change substantially between these states. Each monitoring point should be linked to the tasks performed there so that environmental exposure can be interpreted in relation to workload and duration.

The next stage should integrate the thermal map into a risk-ranking system. Areas with persistent high WBGT, high radiant load, limited airflow, or high physical workload

should receive priority for engineering controls. Workers entering these areas should have clear exposure procedures covering hydration, acclimatisation, recovery, symptom reporting, buddy systems, emergency response, and appropriate clothing. Cheveldayoff et al. (2023) identified monitoring, education, regulation, and cooling strategies as important elements of heat-illness prevention.

Where sufficient field data are available, the logistic model can be recalibrated using measured worker outcomes. Physiological measures such as heart rate, core or surrogate core temperature, skin temperature, body-mass change, or validated heat-strain indicators can provide outcome variables. Ojha et al. (2024) demonstrated the potential of wearable physiological signals for worker-centred heat monitoring, while Ioannou et al. (2022) showed that WBGT is related to several physiological measures. A combined model could therefore use thermofluid exposure, task intensity, work-rest pattern, acclimatisation, and physiological response.

Limitations

The principal limitation is that the numerical worker-level dataset is synthetic, meaning that the reported odds ratios, event proportions, and predicted probabilities are demonstrations of model behaviour rather than empirical findings. The thermofluid inputs are also representative assumptions rather than measurements from a specific gas-fired power plant. These limitations prevent the results from being used to quantify actual occupational risk, establish exposure limits, or claim prevalence among workers.

The thermofluid model is deliberately reduced-order and does not reproduce a full three-dimensional CFD solution of combustion, turbulence, radiation, moisture transport, and equipment conduction. A plant-specific implementation should use measured surface temperatures, equipment geometry, airflow rates, ventilation layouts, weather data, process operating states, and calibrated sensor observations. The model should then be validated against independent measurements at worker locations.

The biostatistical model also uses a small set of predictors and assumes a linear relationship between the log-odds of heat strain and each continuous predictor. Real occupational datasets may require nonlinear terms, interaction effects, repeated-measures methods, random effects for workers, or time-to-event approaches. Future analyses should assess calibration, discrimination, missing data, collinearity, measurement error, and external validation before the model is used for operational decisions.

Finally, WBGT is useful but not a complete representation of individual heat strain. Equivalent WBGT values can arise from different combinations of environmental variables, and recent work has shown that physiological responses can differ between hot-dry and warm-wet environments even at equivalent WBGT (Pryor et al., 2024). A robust plant assessment should therefore retain the underlying temperature, humidity, airflow, radiant temperature, workload, clothing, and exposure-duration measurements rather than storing WBGT as the only exposure variable.

CONCLUSION

This scenario-based study demonstrates a practical route for connecting gas-fired power-plant thermofluid behaviour to worker-centred thermal exposure assessment. The model identified the HRSG area as the highest-exposure scenario, followed by the turbine hall and gas skid, while the control room showed the lowest modelled mean WBGT. The synthetic logistic regression demonstration produced a

positive association between WBGT and modelled heat-strain probability, while metabolic rate also contributed to the predicted risk. The main engineering implication is that worker heat exposure should be assessed at the location and task level because equipment heat, radiant exchange, ventilation, humidity, workload, clothing, and duration can vary considerably within the same plant. The main statistical implication is that environmental measurements can be converted into interpretable probability estimates when worker-level outcome data are available. Future empirical research should replace the synthetic dataset with ethically approved field observations, validate the thermofluid model against sensor measurements, incorporate physiological outcomes, and test the resulting risk model in independent worker populations. For gas-fired power plants operating in warm climates, the preferred control strategy is a hierarchy beginning with reduction of heat transfer from process equipment, followed by effective ventilation and local cooling, exposure-specific work-rest scheduling, acclimatisation, hydration, training, monitoring, and rapid response to symptoms. This approach is consistent with recent occupational heat research while providing an engineering pathway for identifying where thermal controls are most likely to reduce worker exposure.

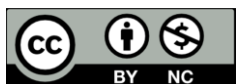
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Table 3: Abbreviations and Units

Abbreviation	Meaning	Unit
CFD	Computational fluid dynamics	—
Clo	Clothing insulation	Clo
HRSG	Heat-recovery steam generator	—
RH	Relative humidity	%
WBGT	Wet-bulb globe temperature	°C
T_a	Air temperature	°C
T_g	Globe temperature	°C
T_{nwb}	Natural wet-bulb temperature	°C
$\dot{Q}$	Heat-transfer rate	W
M	Metabolic heat production	W

SI units were used throughout the manuscript where applicable. Temperature differences and heat-transfer calculations should be reported using internationally accepted units, while WBGT is reported in degrees Celsius because it is an occupational thermal index.



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