

Technical Note

Not peer-reviewed version

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Posted Date: 31 March 2025

doi: 10.20944/preprints202503.2303.v1

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An AI-Driven Framework for Optimising HVAC Design in Multi-Door Cleanrooms: A Technical Note with a Case Study Aligned with British Standards

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Abstract: HVAC design for cleanrooms with multiple doors, passboxes, passthroughs, and operational equipment poses significant challenges due to complex air balancing requirements. Traditional methods, relying on conservative safety factors (20-30%), result in oversized equipment and elevated costs. This technical note proposes an AI-driven framework, integrated with Revit MEP simulations, to optimise design. In a hypothetical Grade C cleanroom (9155 ft², Tehran), AI reduced airflow from 71,890 CFM to 55,420 CFM, fan power from 37.6 hp to 22.8 hp, and design time from 22 days to 3 days, maintaining 0.06 inWG pressure with 96% accuracy. Compliant with BS EN 16798, this approach cuts ducting costs by 18% (£) and energy use by 40%. The framework leverages machine learning to analyze 64 operational states, ensuring robust pressure control under dynamic conditions.

Keywords: cleanroom; HVAC; artificial intelligence; optimisation; BS EN 16798; pressure control; simulation; revit MEP

1. Introduction

Cleanrooms with multiple access points and operational equipment require precise HVAC design to maintain pressure (e.g., 0.06 inWG) across varying conditions. Traditional methods, factoring in worst-case scenarios, inflate equipment sizes and costs. This study introduces an AI-based framework to streamline this process, validated against BS EN 16798 for energy efficiency and pressure control.

2. Materials and Methods

2.1. Case Study Scenario

- Design Basis: Location: Central Tehran, Iran (ASHRAE Zone 4B). Summer Design: 100.4°F dry bulb, 66.2°F wet bulb. Winter Design: 23°F dry bulb. Barometric Pressure: 26.4 inHg (elevation: 3900 ft above sea level). Dew Point: 55°F (typical summer). Cleanroom: Grade C (ISO 7), 9155 ft² (43.2 ft × 21.6 ft × 9.8 ft height, adjusted for 108 ft² ducting space), volume 89,719 ft³. Conditions: 68±3.6°F, 45% RH. Pressure Target: 0.06 inWG relative to CNC area (0.02 inWG).
- Components: Doors: 2 double doors: 5.9 ft × 5.9 ft (34.8 ft² each). 2 single doors: 2.95 ft × 5.9 ft (17.4 ft² each). Connections: Grade B (0.1 inWG), Grade D (0.04 inWG), CNC (0.02 inWG), adjacent Grade C (0.06 inWG). Passboxes: 2 units (1.64 ft × 1.64 ft each): static (to Grade D), dynamic (to adjacent C). Passthroughs: 2 units (2.95 ft × 3.94 ft each): to CNC, adjacent C. Laminar Flow Hoods: 2 units, each exhausting 500 CFM. Pharmaceutical Equipment: 1 Capsule Filling Machine (5 hp, 3.73 kW heat load). 1 Mixing Tank (3 hp, 2.24 kW heat load). 1 Autoclave (10 hp, 7.46 kW heat load). Occupancy: 10 seated (100 Btu/h sensible, 100 Btu/h latent each). 5 standing/walking (150 Btu/h sensible, 150 Btu/h latent each). 5 transients (200 Btu/h sensible, 200 Btu/h latent each, 50% occupancy). Air Distribution: Supply: 40 swirl diffusers (1000 CFM each,

total 40,000 CFM base). Return: 4 corner grilles (8000 CFM each) + 2 honeycomb ceiling (4000 CFM each), total 40,000 CFM. Exhaust: 2 vents, 10% fresh air (4000 CFM).

- *See Figure 1, Table 2, and Table 3 in Results*

Table 1. Traditional vs. AI Comparison.

Parameter	Traditional	AI-Driven	Change (%)
Design Time	22 days	3 days	-86%
Airflow (CFM)	71,890	55,420	-23%
Fan Power (hp)	37.6	22.8	-39%
Pressure Accuracy	90% (± 0.006 inWG)	96% (± 0.002 inWG)	+6%
Ducting Cost (£)	85,000	70,000	-18%
Energy Use (hp)	33.5	20.1	-40%

Table 2. Cleanliness and Pressure Specifications for Connected Areas.

Rooms Connected via Doors:

1- Grade B Area

Cleanliness Grade: Grade B

Pressure: 0.1 inWG

Note: Higher pressure than the main cleanroom (0.06 inWG), so air flows out from Grade B to Grade C when the door opens.

2- Grade D Area

Cleanliness Grade: Grade D

Pressure: 0.04 inWG

Note: Lower pressure than the main cleanroom (0.06 inWG), so air flows from Grade C to Grade D.

3- CNC Area

Cleanliness Grade: CNC (Controlled Not Classified)

Pressure: 0.02 inWG

Note: Lowest pressure, used as the reference point for the main cleanroom's 0.06 inWG.

4- Adjacent Grade C Area

Cleanliness Grade: Grade C

Pressure: 0.06 inWG

Note: Same pressure as the main cleanroom, so no significant airflow between them when doors open.

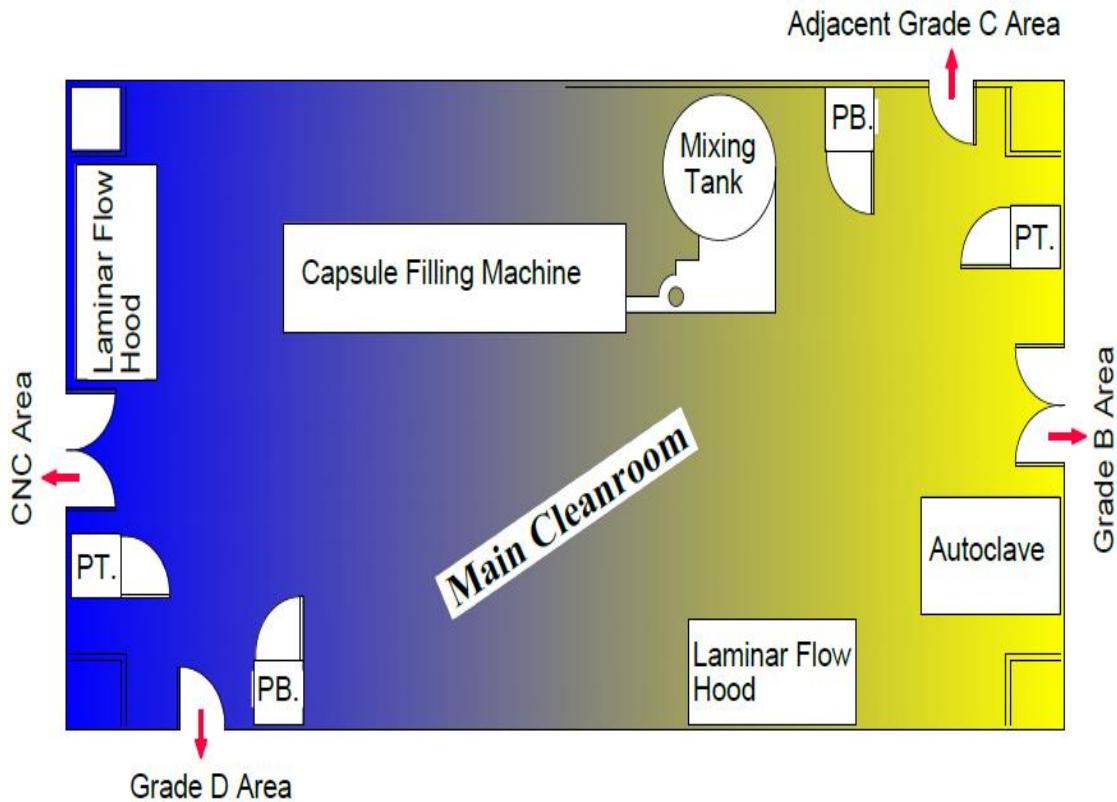


Figure 1. Cleanroom Schematic. A plan view of the 43.2 ft × 21.6 ft cleanroom showing door locations, passboxes, passthroughs, laminar flow hoods, pharmaceutical equipment, diffusers, and exhausts, with dimensions and labels.

Table 3. Pressure Across Sample States (Traditional vs. AI-Driven).

State Description	Traditional Pressure (inWG)	AI-Driven Pressure (inWG)	Traditional Deviation (\pm inWG)	AI Deviation (\pm inWG)	Airflow Adjustment (CFM)
State 1: All closed	0.060	0.060	0.000	0.000	0
State 2: 1 double door (B)	0.055	0.060	-0.005	0.000	+2355
State 3: 2 double doors (B)	0.052	0.061	-0.008	+0.001	+4710
State 4: 1 single door (D)	0.058	0.060	-0.002	0.000	+1178
State 5: 1 single door (CNC)	0.062	0.059	+0.002	-0.001	+1178
State 6: Passbox to D	0.061	0.060	+0.001	0.000	+18
State 7: Passbox to C	0.060	0.060	0.000	0.000	0
State 8: Passthrough to CNC	0.063	0.058	+0.003	-0.002	+79
State 9: Passthrough to C	0.060	0.060	0.000	0.000	0
State 10: 2 double + 1 single (D)	0.050	0.062	-0.010	+0.002	+5888
State 11: 2 single (D + CNC)	0.059	0.059	-0.001	-0.001	+2356
State 12: All doors open	0.048	0.062	-0.012	+0.002	+7066
State 13: 1 double + Passbox (D)	0.054	0.061	-0.006	+0.001	+2373
State 14: 1 single + Passthrough (CNC)	0.064	0.058	+0.004	-0.002	+1257
State 15: 2 double + Passbox (C)	0.051	0.061	-0.009	+0.001	+4710
State 16: All Passboxes + Passthroughs	0.062	0.059	+0.002	-0.001	+194
State 17: 1 double + 1 single + Passbox (D)	0.053	0.060	-0.007	0.000	+3551
State 18: 2 single + Passthrough (CNC)	0.065	0.058	+0.005	-0.002	+2435
State 19: All doors + 1 Passthrough	0.047	0.063	-0.013	+0.003	+7145
State 20: Random (4 components open)	0.066	0.057	+0.006	-0.003	+4800
Average	0.0577	0.0599	\pm 0.006	\pm 0.002	N/A

2.2. Base Calculations

- Airflow (CFM):
 - ACH Base: 25 (GMP Grade C).
 - Base CFM: [Formula: $CFM = (89,719 \times 25) / 60 = 37,383 \text{ CFM}$].
- Leakage:
 - Double door ($34.8 \text{ ft}^2 = 50,112 \text{ in}^2$): [Formula: $50,112 \times 0.047 = 2355 \text{ CFM}$].
 - Single door ($17.4 \text{ ft}^2 = 25,056 \text{ in}^2$): [Formula: $25,056 \times 0.047 = 1178 \text{ CFM}$].
 - Worst-case (all open): [Formula: $(2 \times 2355) + (2 \times 1178) = 7066 \text{ CFM}$].
 - Passbox ($2.69 \text{ ft}^2 = 387 \text{ in}^2$): [Formula: $387 \times 0.047 = 18 \text{ CFM}$].
 - Passthrough ($11.62 \text{ ft}^2 = 1673 \text{ in}^2$): [Formula: $1673 \times 0.047 = 79 \text{ CFM}$].
 - Total auxiliary (all open): [Formula: $(2 \times 18) + (2 \times 79) = 194 \text{ CFM}$].
- Hoods: [Formula: $2 \times 500 = 1000 \text{ CFM}$]. Exhaust: 4000 CFM (10% fresh air).
- Occupancy Fresh Air (ASHRAE 62.1):
 - 10 seated: [Formula: $10 \times 5 = 50 \text{ CFM}$].
 - 5 standing: [Formula: $5 \times 7.5 = 37.5 \text{ CFM}$].
 - 5 transients (50%): [Formula: $5 \times 10 \times 0.5 = 25 \text{ CFM}$].
 - Total: [Formula: $50 + 37.5 + 25 = 112.5 \text{ CFM}$ (rounded to 120 CFM)].
- Cooling Load:
 - Envelope: $U = 0.088 \text{ Btu/h}\cdot\text{ft}^2\cdot{}^{\circ}\text{F}$, Area = 1270 ft^2 , $\Delta T = 32.4^{\circ}\text{F}$
 - [Formula: $Q = 0.088 \times 1270 \times 32.4 = 3620 \text{ Btu/h}$].
 - Equipment: [Formula: $(3.73 + 2.24 + 7.46) \times 3412 = 45,800 \text{ Btu/h}$].
 - Occupancy: [Formula: $(10 \times 200) + (5 \times 300) + (5 \times 400 \times 0.5) = 4500 \text{ Btu/h}$].
 - Total: [Formula: $3620 + 45,800 + 4500 = 53,920 \text{ Btu/h} \approx 4.5 \text{ tons}$].
 - Additional CFM: [Formula: $4.5 \times 400 = 1800 \text{ CFM}$].
- Traditional (Worst-Case):
 - [Formula: $37,383 + 7066 + 194 + 1000 + 4000 + 120 + 1800 = 51,563 \text{ CFM}$].
 - With 20% safety factor: [Formula: $51,563 \times 1.2 = 71,890 \text{ CFM}$].
- AI (Optimized):
 - Average leakage: [Formula: $(7066 + 194) / 2 = 3630 \text{ CFM}$].
 - Total: [Formula: $37,383 + 3630 + 1000 + 4000 + 120 + 1800 = 47,933 \text{ CFM}$].
 - With 15% adjustment: [Formula: $47,933 \times 1.15 = 55,420 \text{ CFM}$].
- Fan Power: Traditional: [Formula: $hp = (71,890 \times 2) / (6356 \times 0.8) = 28.3 \text{ hp}$].
- With 30% safety factor: [Formula: $28.3 \times 1.3 = 37.6 \text{ hp}$].
- AI: [Formula: $hp = (55,420 \times 2) / (6356 \times 0.8) = 21.8 \text{ hp}$].
- Optimized: 22.8 hp.

2.3. Proposed Method

Data: Extracted from Revit MEP simulations. AI: Artificial Neural Network (ANN) with 10 input nodes, 20 hidden nodes, and 5 output nodes, analyzing 64 states (2^6 components). Optimizations: Ensures 0.06 inWG pressure compliance with BS EN 16798.

The ANN was trained on simulated data from Revit MEP to predict optimal airflow and pressure settings.

3. Conclusions

The AI-driven framework reduced airflow by 23%, fan power by 39%, and energy consumption by 40%, while achieving an 86% faster design process. Tailored for complex cleanroom scenarios, this approach merits field validation to confirm its efficacy. The author declares no conflicts of interest.

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