Ambient Intelligence (AmI) Assisted Passive Ventilation in Mixed-Use Micro Apartment During SARS-CoV-2 Pandemic

Dženis Avdić

Faculty of Architecture, Architectural Structures and Building Technology Department,
University of Sarajevo,
Patriotske lige 30, 71000 Sarajevo, Bosnia and Herzegovina
E-mail: dzenis.avdic@af.unsa.ba

Abstract: During recent and ongoing pandemic circumstances, a lot of architectural spaces were adapted for use not designed for. Besides ergonomics and comfortable furniture, occupational health hazards include more indoor air pollution induced by functionally over-saturated architectural spaces. This paper discusses options and proposes an algorithm to improve air quality inside mixed-use micro apartment using low energy consumption embedded artificial intelligence (AI) systems to assist users in passive ventilation usage. Through data collected for observed case, algorithm is explained and tested both in terms of feasibility in low power embedding and energy efficiency annual savings by using assisted passive ventilation. Air pollution and progressively unsustainable old, built-in materials and infrastructural systems in existing buildings with limited to none energy upgrade options need solutions for maintaining comfortable and healthy indoor environmental conditions. Proposed low power embedded, ambient intelligence system provides solutions for such architectural spaces. Case study included a variety of parameters in a complex physical model, and through data feature engineering most influential parameters were chosen. Time series forecasting for predictive maintenance of air quality and built-in materials was tested through three different models: ARIMA, Facebook's Prophet and Tensorflow recurrent neural network (RNN) with gated recurrent units (GRUs). Machine learning algorithm (TinyML) was deployed to Arduino Nano 33 BLE Sense microcontroller board in testing phase, to prove simplicity and feasibility of chosen AI neural network. Validation is provided through simulation on collected data, to show ventilation energy savings by using AI assisted passive ventilation.

Keywords: passive ventilation; artificial intelligence; low power; embedded system;

1 Introduction

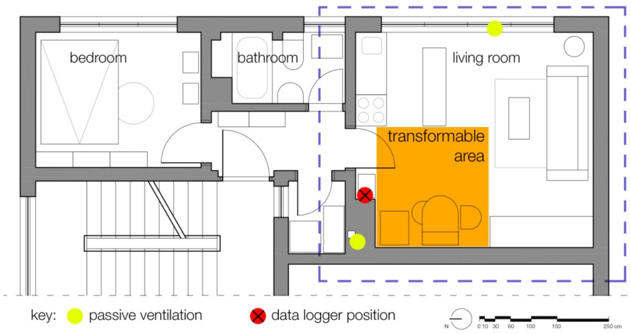
Global SARS-CoV-2 pandemic influenced not only industries, companies, stock market and education, but also architectural spaces and our lifestyles (Horvat, Ávila, 2020). Government issued lockdowns forced a lot of people to work from home, and to adapt living and lounge areas to small home offices. Struggling to make spaces comfortable and flexible for mixed-use and efficient and productive working hours, people kept forgetting about health impacts this adaptation implied.

Besides ergonomics and comfortable furniture, health impacts include more indoor air pollution induced by functionally over-saturated architectural spaces. This issue is underlined in small spaces inside old uninsulated buildings (Arnautović – Aksić, et al., 2016) where self sustainability is hard to achieve.

This paper discusses options and proposes an algorithm to improve air quality inside mixed-use micro apartment using low energy consumption embedded artificial intelligence (AI) systems to assist users in passive ventilation usage. Case study is conducted for micro apartment located inside residential building originally built in 1970s for workers in small industrial town of Vogošća (near Sarajevo, Bosnia and Herzegovina).

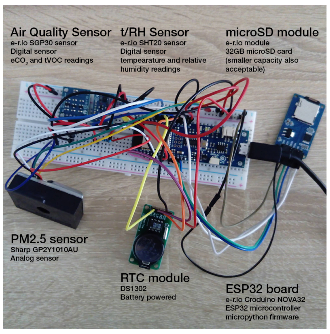
Original 35 m^2 layout was designed to accommodate single user and was composed of living room and kitchen/dining room with one bathroom and small storage space. This apartment, dated from Socialist Federal Republic of Yugoslavia period, was later adapted for young families, where kitchen is relocated to living room, and dining area is converted to bedroom. Small storage space was converted to walk-in closet that also includes dryer. Research is conducted within mixed-use 19 m^2 living room area, now composed of small kitchenette, transformable table to accommodate dining area, and lounge space (figure 1). During pandemic conditions, transformable dining table was also used for home office.

Figure 1 The floor plan of observed space (author)



Data was collected during months of winter 2020/2021 season. Data logger (Avdić, 2020) was built upon Croduino Nova (ESP32) microcontroller with SGP30 air quality sensor, SHT20 temperature/relative humidity sensor and analog optical dust PM2.5 sensor programmed in Micropython (figure 2a). Sensor data was written in 15 minute intervals on microSD card, including web data from local weather and air quality stations. In preprocessing phase, data was cleaned up and merged to hourly logs (figure 2b).

Figure 2 a) left – data logger sensors and components, b) right – hourly log and column names (author)



	ds	dan	temp	r_hum	co_2	aqi_i	temp_e
0	2020-12-28 01:00:00	1.0	26.262567	40.976413	728.598900	67.941840	2.410
1	2020-12-28 02:00:00	1.0	25.984767	40.775907	675.325533	65.810073	2.890
2	2020-12-28 03:00:00	1.0	25.831253	40.658130	659.029267	64.538170	2.885
3	2020-12-28 04:00:00	1.0	25.716143	40.527917	642.445900	64.224107	4.110
4	2020-12-28 05:00:00	1.0	25.571363	40.354333	638.112600	64.128677	5.000

	ds	r_hum_e	press	wind_s	wind_a	aqi_e	a_hum
0	2020-12-28 01:00:00	100.000000	998.0	7.200000	130.0	60.666667	0.010100
1	2020-12-28 02:00:00	100.000000	998.0	4.600000	120.0	52.000000	0.009896
2	2020-12-28 03:00:00	96.500000	999.0	5.400000	155.0	40.333333	0.009783
3	2020-12-28 04:00:00	90.666667	999.0	7.700000	150.0	21.000000	0.009689
4	2020-12-28 05:00:00	84.000000	999.0	5.633333	100.0	11.666667	0.009570

columns:
ds - datetime format time stamp, **dan** - day of week
temp - interior ambient temperature (°C)
r_hum - indoor relative humidity (%)
co_2 - CO_2 concentration (ppm), **aqi_i** - interior air quality (µg/m³)
temp_e - external (outdoor) temperature (°C)
r_hum_e - outdoor relative humidity (%)
press - atmospheric pressure (hPa)
wind_s - wind speed (m/s), **wind_a** - wind direction angle
aqi_e - exterior (outdoor) air quality index
a_hum - absolute interior humidity - water vapour content (kg/m³)

Since the apartment was used 24/7 for different activities that introduced more moisture, CO2 and airborne dust (particulate matter) into the air, indoor air quality self sustainability was at stake. To prevent pollution build up, and to enable enough fresh air for productive and healthy environment, ambient intelligence (AmI) assisted system (Haque, et al., 2020) for passive ventilation control was discussed, along with all limitations existing building already had (non-insulated building envelope, old built-in materials, and highly sealed upgraded windows).

2 Data Analysis

2.1 Infiltration

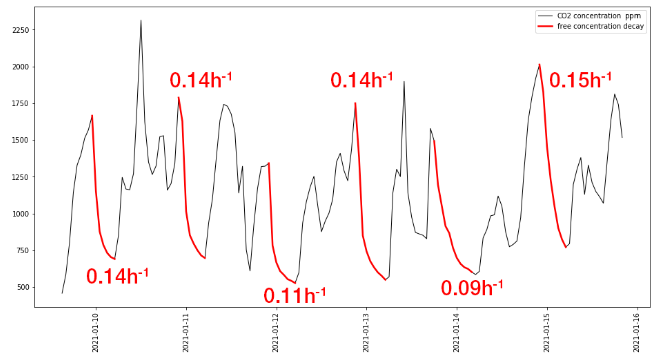
To estimate infiltration energy losses and calculate approximate air change rate due to constant natural infiltration (through enclosure and around sealed windows) CO_2 log was taken into consideration on logarithmic y-scale plotted against time intervals on x-axis to fit and calculate slope representing air change rate (Howard-Reed, et al., 2002):

$$\ln\left(\frac{C(t)}{C(0)}\right) = -nt, \qquad \text{(eq. 1)}$$

where C(0) is initial concentration, C(t) is concentration after time period t, and n is air change rate (h^{-1})

Natural decay of excessive carbon dioxide (Ferdyn-Grygierek, et al., 2019) and water vapour during night dormant hours, when heating system was off, was observed. For selected data frame, average of 0.08 h^{-1} air change rate was calculated, with usual 0.13 h^{-1} rate during colder nights (higher pressure difference).

Figure 3 CO_2 concentration log example plotted using Python's mathplotlib and natural concentration decay (red) used for air change rate calculation (author)

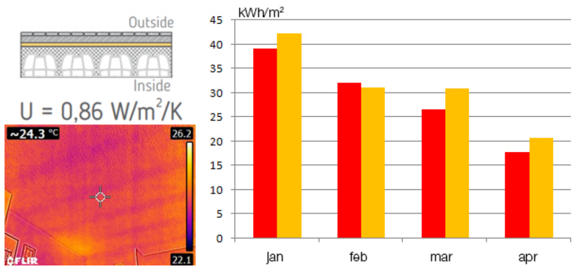


As shown in figure 3, dormant hours time period, with low average air change rate due to highly sealed facade openings, is insufficient to provide enough fresh air with natural infiltration concentration decay, so stale and polluted air is building up as time progresses. This issue is accented during winter months when outdoor air pollution in Sarajevo area is usually high (IQAir, n.d.).

2.2 Building Physics Audit

Physical characteristics of observed architectural space were simulated using iSBEMba model (BRE Group, n.d.) using historically based assumptions for built-in materials and compared to thermal imaging audit results obtained in-situ (figure 4a). Simulated annual energy consumption is compared to depleted energy through observed time period (figure 4b).

Figure 4 a) top left – historically determined typical details (Arnautović – Aksić et al., 2016) were compared with thermal images (bottom left) to estimate enclosure U values, b) right – simulated results were compared to real data for validation



This confirmed average U-value of 1.14 W/m²K for apartment enclosure (Arnautović – Aksić et al., 2016) in observed space, along with critical thermal bridges in facade walls for dew point calculation. Based on U-value and temperature difference we can determine interior surface temperature (T_w) for recognized critical points (Hadrović, 2010):

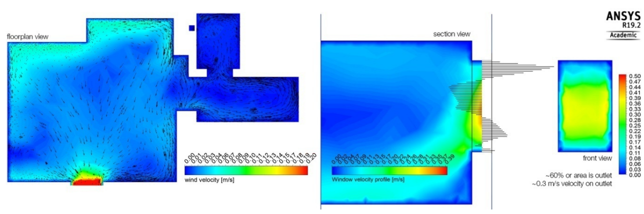
$$\alpha_i(T_i - T_w) = U(T_i - T_e) \Longrightarrow$$

$$\Longrightarrow T_w = T_i - \frac{U(T_i - T_e)}{\alpha_i} = T_i - \frac{U\Delta T}{\alpha_i} \qquad \text{(eq. 2)}$$

2.3 CFD Passive Ventilation Potential

Passive ventilation potential is analysed using ANSYS Fluent computational fluid dynamics (CFD) simulation software. To determine air change rate, simulation is conducted for usual passive ventilation setup through window opening and passive ventilation shaft (shown in figure 1). Since all openings in observed space are on east facing facade, east wind log profile was taken as a reference for modelling. East winds spectrum was also most common in Sarajevo area, which is confirmed with logged data, so the mean wind speed value was modelled into simulation.

Figure 5 Estimating passive ventilation efficiency coefficient using ANSYS Fluent CFD simulation software (author)



Simulation (figure 5) provided insight into actual flow efficiency coefficient for calculating air change rate based on east wind vector component perpendicular to facade opening (Swami, Chandra, 1987):

$$ACH = \frac{Q}{V}\,[h^{-1}]$$

where $Q = c_{eff} \cdot A_{opening} \cdot v_{ref} \left[\frac{m^3}{s}\right]$ (eq.3)
and V[m³] is volume of air in a room

Exchange air flow efficiency coefficient (c_{eff}) was estimated to be around 0.1, which was coded into ACH calculation (eq. 3) for real-time variable velocity vector magnitudes. After that, required time duration for passive ventilation is estimated using eq. 1. During that time, mixing of cold outdoor and warm indoor air is occurring, so estimation for energy required to maintain interior ambient temperature could be calculated using Mollier diagram or approximated using heat loss calculation due to ventilation in one hour (The Open University, n.d.):

$$Q_{HL} = 0.33 \cdot n \cdot V \cdot \Delta T\ [W] \qquad \text{(eq.4)}$$

where 0.33 is energy required for heating up 1 m³ of air for 1 K

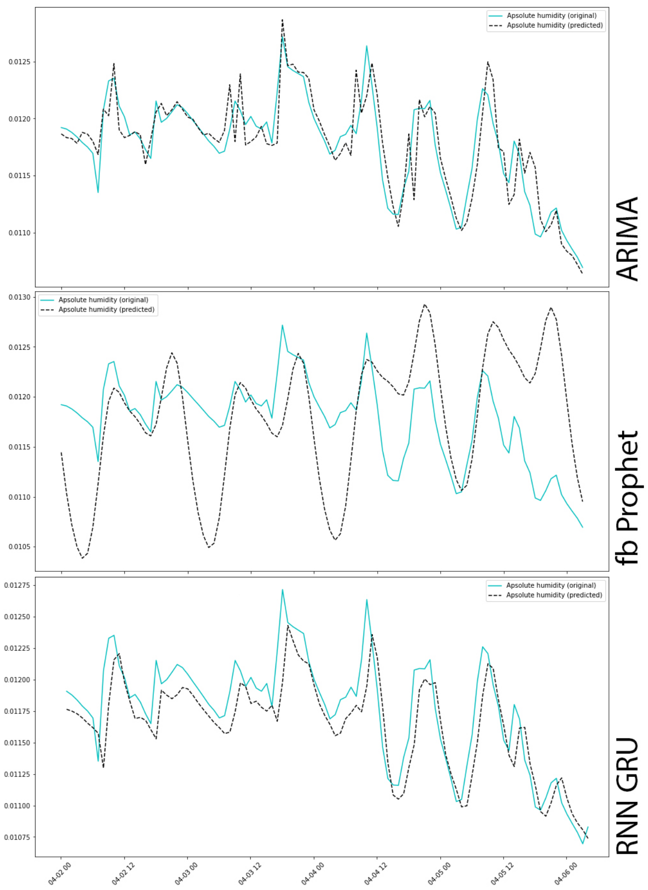
For code implementation purpouses, eq. 4 is chosen over Mollier diagram calculation.

2.4 Time Series Forecasting Algorithms

Activities inside observed space introduce water vapour, CO_2 and airborne dust (PM2.5), so correlation matrix for logged features was observed to confirm interdependence between these three parameters. As temperature/relative humidity sensor is most commonly available and affordable compared to CO_2 and PM2.5 sensors, water vapour content of interior air was chosen for univariate machine learning models in time series forecasting. Since observed space was uninsulated and with old built-in materials, this feature was used to estimate vapour condensate and mold growth potential. Along with this phenomenon, airborne dust and spores released into the air were going to be prevented. The concept discussed and proposed is based on predictive maintenance for built-in materials with prolonged life span, but also implies indoor air quality and comfort improvement.

Three different algorithms for time series data analysis and forecasting were compared and discussed. Statistical ARIMA (autoregressive integrated moving average) model was implemented and compared both to FFT (fast Fourier transform) decomposition based Facebook's Prophet predicting algorithm and RNN (recurrent neural network) machine learning model with GRUs (gated recurrent units) for univariate time series forecasting of absolute humidity of interior air. These three algorithms shown mean absolute error (MAPE) of 2.7%, 7.5% and 2.1% respectively (figure 6), but for easier implementation onto microcontroller, RNN TinyML univariate model was chosen (Lazzeri, 2021). Even though ARIMA model was quite accurate (MAPE 1.8% for one step prediction), significant computational cost made it inoperable on microcontrollers. Besides that, argument contra ARIMA is also that it requires clean input data set and mostly manual preprocessing. Although Prophet was flexible and easy to implement, accuracy was an issue for chosen data features. Both accuracy and computational cost of RNN with GRUs made it feasible to implement onto microcontroller.

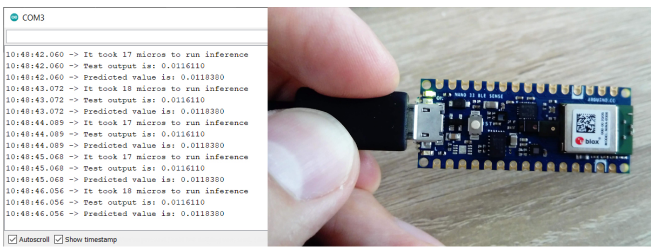
Figure 6 Forecasting accuracy comparison for three observed algorithms



2.5 Proposed Low Power System

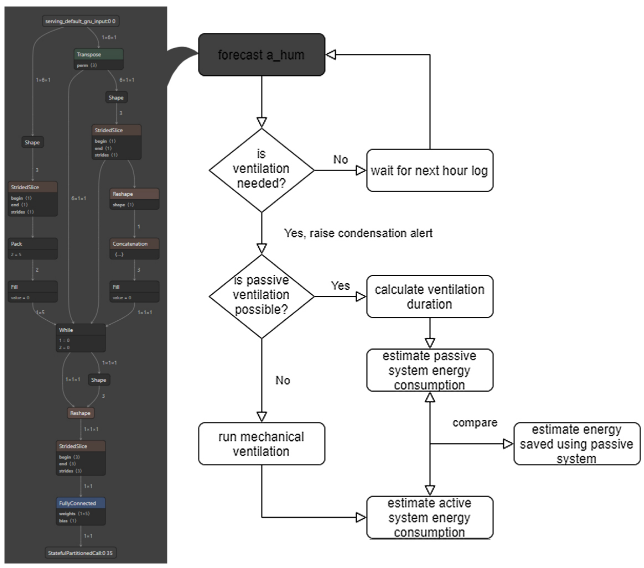
For a proof of concept (POC), TinyML (machine learning for microcontrollers) model was deployed to Arduino Nano 33 BLE Sense board with built-in sensors using Tensorflow based EloquentTinyML Arduino library to estimate ambient intelligence (AmI) system auxiliary energy consumption (figure 7). As an alternative, for more advanced system and proposed algorithm, Arduino Nano is exchanging data with logger shown in figure 2, so energy consumption of logger is to be taken into account as well. In terms of energy required for ventilation, auxiliary energy depleted by proposed Arduino microcontroller is shown to be neglected.

Figure 7 Testing of deployed time series forecasting model on Arduino Nano 33 BLE Sense microcontroller (author)



Proposed algorithm concept (figure 8) for microcontroller uses TinyML neural network to forecast absolute humidity (vapour content of interior air) for next hour log. Enclosure interior surface temperature (T_w) is than calculated using eq. 2. For temperature T_w, relative humidity is calculated using forecasted value to determine if it's exceeding 75% dew point value (mold growth potential). For values exceeding 75%, UI (user interface) alert is raised and possibility of using passive ventilation (air quality index (AQI) outside is acceptable, and there's no percipitiation or high humidity) is checked. If passive ventilation is possible, required ventilation duration is calculated by solving eq. 1 for time t, and using ACH (n) from eq. 3 for current wind parameters (magnitude of wind vector component perpendicular to facade). For short required time (less than 15 minutes), algorithm assumes near zero energy required for ventilation due to accumulated heat in furniture and built-in materials. For longer air exchange it calculates heat loss energy using eq. 4. Finally, energy required both for active and passive systems is calculated to estimate energy savings.

Figure 8 Proposed algorithm for microcontroller (TinyML on Arduino Nano 33 BLE Sense using data from logger shown in figure 2) (author)



3 Conclusion

Validation of proposed algorithm was calculated using data collected over 15 weeks of winter season inside observed space. Total energy saved by using AmI assisted passive ventilation calculated in algorithm simulation was estimated to be up to 18.7% of total energy required for ventilation. In some cases, for long lasting air exchange, passive ventilation was proven to be inefficient, because energy required for heating up cold air mixture was up to 20 times higher than energy required for operating active ventilation system. But, for most existing old and uninsulated buildings, without energy upgrades both in enclosing structure and built-in infrastructure systems, just like in case observed, passive ventilation is the only way to keep interior space healthy and comfortable. Application of proposed low power embedded AI system is possible and feasible for historical buildings and buildings with limited options for energy upgrades, as well as for limited upgrades in built-in materials and active ventilation systems.

When space is not designed to accommodate multiple functions in mixed-use manner, it has to be controlled in some way. This also applies for conserved historical buildings with prolonged life cycle built-in materials. As architectural space is complex physical system for users to be able to predict and control certain parameters, artificial intelligence is to be integrated as helping hand for maintenance of comfortable and healthy environmental conditions. Every architectural space is unique physical system, so ambient intelligence (AmI system) is required to be proposed based on detailed analysis of multiple parameters in terms of building physics and fluid dynamics and carefully installed and maintained for different weather seasons.

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Biographical notes:

Dženis Avdić is born in 1989 in Sarajevo. He earned his Master of Architecture degree in 2013 from Faculty of Architecture, University of Sarajevo. He's currently employed as Senior Assistant at Architectural Structures and Building Technology Department of Faculty of Architecture in Sarajevo and continues his education towards PhD degree. His research involves energy efficiency of historical buildings through implementation of smart solutions in existing structures. Recent bibliography includes studies on Austro-Hungarian heritage buildings in Bosnia and Herzegovina. Heritage historical buildings are also main theme of his artworks.