# A COMPUTATIONAL MODEL OF A SENSOR NETWORK FOR THE OPTIMIZATION AND CONTROL OF ACOUSTICAL PERFORMANCE CRITERIA IN SPATIAL ENCLOSURES

GANAPATHY MAHALINGAM
*North Dakota State University, Fargo, North Dakota, U.S.A.*
*Ganapathy.Mahalingam@ndsu.edu*

**Abstract.** The technology of nanoblock-based circuits is enabling the creation of ultra-small sensors that can transmit their location and readings using radio frequencies. This technology has the potential to enhance the optimization of environmental performance criteria in spatial enclosures, using a wide range of actuators that function at different scales. The combination of such ultra-small sensors with actuators will enable the creation of spatial enclosures that are complex adaptive systems, which dynamically optimize the various environmental performance criteria for the enclosures. Defining a model for the optimization process in these systems presents significant challenges. This paper will set out a model for the use of ultra-small sensor systems in optimizing environmental performance criteria in spatial enclosures, especially acoustical performance criteria.

## 1. Introduction

The technology of nanoblock-based circuits is enabling the creation of ultra-small sensors that can transmit their location and readings using radio frequencies. This technology has the potential to enhance the optimization of environmental performance criteria in spatial enclosures, using a wide range of actuators that function at different scales. These actuators range from material modifiers that use piezoelectric effects to micro-electrical mechanical systems to motors that move large panels. The combination of such ultra-small sensors with actuators will enable the creation of spatial enclosures that are complex adaptive systems, which dynamically optimize the various environmental performance criteria for the enclosures. Defining a model for the optimization process in these systems presents significant challenges. This paper will set out a model and relevant challenges for the use of ultra-small sensor systems that are combined with actuators to optimize environmental performance criteria in spatial enclosures. This model will enable the consideration of architectural space as a dynamic, adaptive entity rather than as a static entity, which has been the traditional approach. This model also has the potential to serve a broader range of optimization problems in other contexts as well.

## 2. Sensors and Effectors

### 2.1. NANOBLOCKS AND ULTRA-SMALL SENSORS

Nanoblocks are substrates for circuit components at the scale of nanometers. These nanoblocks are the size of pepper flakes. These blocks are combined into ultra-small circuits that can function as a sensor or be part of an actuator. A sensor measures some environmental criterion. An actuator takes the measurement or reading of a sensor and performs an action through electrical and mechanically driven devices. An actuator may have a digital signal processor as part of its configuration. These nanoblock-based ultra-small sensors can be so ubiquitous as to form a coat of ‘sensor paint’ on surfaces of spatial enclosures.

### 2.2. SENSOR ARRAYS AND NETWORKS

Since the ultra-small sensors are so small that thousands could be placed in one square inch, their individual readings may be so close to each other that they are not significantly different from each other. This allows the combination of many sensors into sensor arrays using statistical techniques such as cluster analysis. Cluster analysis is a statistical technique that groups entities together such that the within-group variation is minimized and between-group variation is maximized. These sensor arrays can be dynamically defined based on a cyclic sampling of the sensor readings, performing the cluster analysis, and grouping sensors into sensor arrays. In the case of steady-state criteria, these sensor arrays are fairly stable in terms of their boundaries, but in dynamic criteria, the boundaries of the sensor arrays may vary in time. The same process can also be used for the actuators if the actuators are at the same scale as the sensors.

These sensor arrays or ‘zones’ can communicate with each other using radio frequency waves, exchange information, and create ad-hoc networks of measurements. Optimization of environmental performance criteria in the spatial enclosures is modeled as an optimization based on this network of measurements.

### 2.3. EFFECTORS

An effector is a complex entity that produces an effect on another entity or on the environment. An effector is a sensor-actuator pairing. It combines, at a minimum, one sensor with one actuator. Other configurations that are possible are the coupling of one sensor with many actuators, many sensors with one actuator, and many sensors with many actuators. The actuator performs its action based on the readings from one or more sensors. This actuation process can utilize computation or other forms of processing of the sensor data. The optimization, both spatial and temporal, of readings from multiple sensors requires sophisticated techniques. The sensor can simply be a measuring instrument that record measurements of different kinds. Sensors are available that can measure temperature, humidity, mass airflow, position, etc. An actuator can range in scale from one that does molecular manipulation to micro electro-mechanical systems to large scale motor-based kinetic systems.

## 3. Environmental Performance

### 3.1. ENVIRONMENTAL PERFORMANCE CRITERIA

The environmental performance criteria of interest to designers of spatial enclosures for various purposes are illumination levels, sound frequencies, sound amplitude, sound intensities, temperature and humidity. These performance criteria correspond to the human senses of sight, hearing and touch respectively. Being able to optimize these criteria in complex spatial enclosures will enhance human activities in those enclosures in transparent and subtle ways.

For example, patrons sitting in a library carrel and reading books will not notice that these ultra-small sensors have recorded the illumination levels on their desktops and signalled the lights overhead to increase their brightness. Concert goers in a concert hall will not notice the detection of an echo condition and its cancellation by a network of actuators controlled by sensors on the surfaces of the spatial enclosure of the auditorium. A homeless man will not realize that the park bench he is approaching is being warmed up for him to curl on as he approaches the bench.

### 3.2. STEADY-STATE AND DYNAMIC ENVIRONMENTAL PERFORMANCE CRITERIA

A steady-state environmental performance criterion is one that does not vary significantly over time, unless a change is made to one of its causal agents. A dynamic environmental performance criterion is one which varies in time. The time cycles can range from mere milliseconds or seconds in the case of sound, to a year in the case of temperature. Illumination levels in a spatial enclosure are steady-state phenomena. Unless the light sources are changed, the illumination levels stabilize in a very short duration after the light sources are turned on. The only exception to this is daylight which causes illumination levels to vary over a time cycle. Temperature variation is similarly a steady-state phenomenon, especially in interior spatial enclosures. Temperature variation can be a dynamic phenomenon if the spatial enclosure has a membrane exposed to the exterior, which has a dynamic temperature range over a time cycle.

## 4. Optimization

### 4.1. OPTIMIZATION OF ENVIRONMENTAL PERFORMANCE CRITERIA

Optimization can be simply defined as the maximizing or minimizing of a particular quantity, in this case, the measurements of various environmental performance criteria recorded by the various sensors.

The spatial distribution of sensors makes it necessary to consider the spatial effect of the optimization. A local optimization has global effects, and global optimization has local effects. This spatial effect can be resolved using relatively simple techniques in the case of steady-state criteria. The optimization becomes very complex when the criteria are dynamic and change over different time cycles. For example, sound changes over time cycles measured in millisecond intervals and temperature varies over time cycles measured in hours.

Optimization of environmental performance criteria is complicated by the fact that human preferences are often based on aggregate measurements of the environmental performance criteria rather than instantaneous measurements. For example, human preferences for acoustical conditions are based on the ratio of sound energy summations over time intervals, rather than the instantaneous sound energy variation in time, as would be indicated by an energy response graph.

### 4.2. RESOLVING THE SPATIAL EFFECTS OF SOURCES AND EFFECTORS

The optimization of the environmental performance criteria depends to a large extent on the resolution of the spatial effects caused by the sources (light fixtures, sound sources, heat sources, etc.) and the spatial effects caused by the surfaces that make

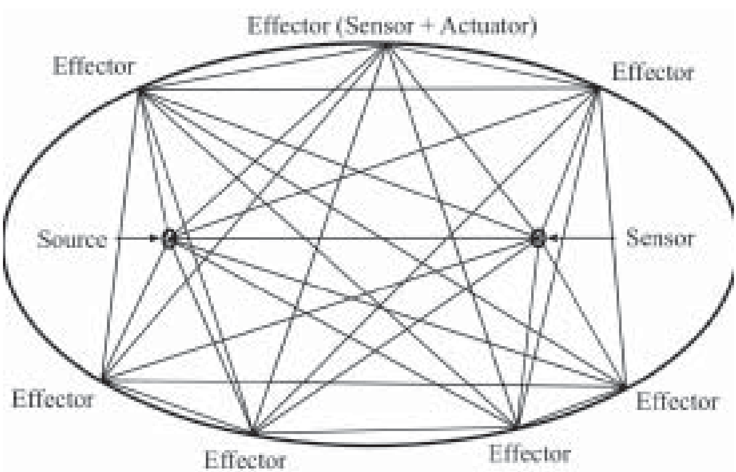


*Figure 1.* Diagram of a system showing a single source, a set of effectors (sensor-actuator pairs) and a performance sensor. This system is called an optimaton.

up the enclosure. The measurement at a particular sensor at a particular time can be modelled as a vector of the spatial effects of the various sources and surfaces that are part of the spatial enclosure. All the vectors are convolved in time to produce the dynamic variation of criteria at a particular sensor location.

An optimization network that links a single source, effectors and a single performance sensor is called an *optimaton*. An *optimaton* behaves like a neural network in that the source acts as an input, the network of effectors optimizes the effect of the source or “transforms” the source and the performance sensor receives the output of the transformation. Multiple *optimatons* can be linked to form meta-networks by networking the sources or the performance sensors.

The mathematical model for the spatial effect of multiple sources in a spatial enclosure made up of a finite number of surfaces can be modelled as follows:

1. Let us say there are m sources $S_1 ... S_m$.

2. Let us also say that there are n surfaces $E_1 ... E_n$ such that each functions as an effector (sensor-actuator pair), and

3. Let us measure performance characteristics at one performance sensor R.

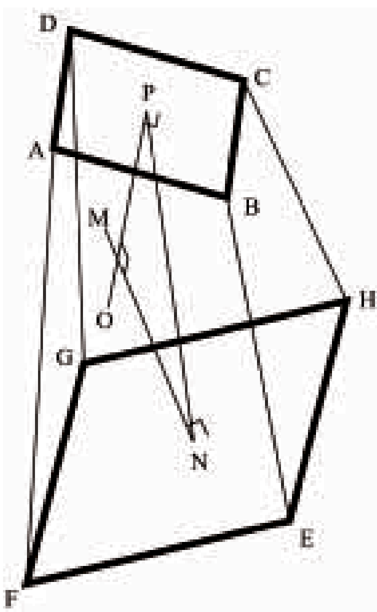


*Figure 2.* Diagram showing the form factor between two components.

The spatial relationship between any two components of an optimization network is called its form factor. Form factors establish the spatial effect between a source and an effector, or between an effector and another effector, between a source and a performance sensor, and an effector and a performance sensor. Figure 2 shows the form factor relationships between any two components in the model.

In Figure 2, ABCD and EFGH are two components. MN and OP are the normals to the two components at their centroids. NP is the distance between the two components. The angle between the two components is the angle between the normals. To derive the form factor between the two components, the following relations are taken into account:

1. The radiation between the components is directly proportional to the ratio of their areas. This can also be modelled as being proportional to the solid angle subtended by the two components.
2. The radiation between the two components is inversely proportional to the square of the distance between the components.
3. The radiation between the two components is proportional to the cosine of the angle between the two components.

The form factor for the two components will then be: $(A_{abcd}/A_{efgh})*(1/D_{np}{}^{2)}*(\cos\theta)$

For a situation where there is a single source, n effectors and one performance sensor, there are the following form factors:

1. Source to performance sensor (SR)
2. Source to all effectors ($SE_1...SE_n$)
3. Each effector to all other effectors ($E_1E_2...E_1E_n$)
4. Each effector to the performance sensor ($E_1R...E_nR$)

These form factors can be written as a sum of vectors: $V(SR) + V(\Sigma_{1\text{ to }n}\ SE_n) + V(\Sigma_{1\text{ to }n}\ E_n\Sigma_{1\text{ to }n\text{-}1}\ (E_{n+1})) + V(\Sigma_{1\text{ to }n}\ E_nR)$. These form factors add up to a total of $(1) + (n) + n(n\text{-}1) + (n) = n^2 + n + 1$ form factors.

The radiation sequence from the sources to the effectors to the performance sensor can be modelled. In this model:

1. Energy is radiated from the source to the performance sensor.
2. Energy is radiated from the source to all the effectors in the spatial enclosure.
3. Energy is radiated from all the effectors to the performance sensor.
4. Energy is radiated from each effector to all other effectors.
5. Energy is radiated from all effectors to the performance sensor.
6. Steps 4 and 5 are repeated till the energy is dissipated.

Steps 1–5 are defined as constituting the primary propagation. This propagation engages all form factors at once. The energy is therefore multiplied by $(n^2 + n + 1)$ form factors for this primary propagation. After this propagation, the secondary propagation is a repetition of the radiation from each effector to all other effectors, and from all effectors to the performance sensor (steps 4 and 5). This represents $n(n - 1) + n = n^2$ form factor calculations per cycle. This propagation cycle is repeated at the required frequency f. Therefore the total number of form factor computations for energy propagation is $((n^2 + n + 1)+(n^2)f)$ if there are no form factor updates required by changes in effectors. For m sources there are $m((n^2 + n + 1)+(n^2)f)$ form factor computations for the propagation. This is a polynomial and can be computed in polynomial time.

This process is complicated by the fact that any change at an effector will affect the subsequent propagation. If an effector changes in a single propagation cycle, then the following form factors change:

1. That effector to all other effectors.
2. That effector to the performance sensor.
3. That effector to the source.

This represents an update of (n-1) + (1) + (1) = (n + 1) form factors for the next propagation cycle. If all effectors change in one cycle, then the following form factors will change:

1. All effectors to each other.
2. All effectors to performance sensor.
3. Source to all effectors.

This represents an update of n(n - 1) + (n) + (n) = ($n^2$ + n) or n(n + 1)form factors for the next propagation cycle. The algorithm for energy propagation will be as follows:

1. Start with energy Q.
2. Multiply Q by vectors of a total of ($n^2$ + n + 1) form factors.
3. Record energy and time of arrival at the performance sensor, after multiplication by vectors that end in performance sensor.
4. Update n(n + 1) form factors, where n is the number of effectors that have changed.
5. Multiply Q by vectors of a total of ($n^2$) form factors.
6. Update/record energy and time of arrival at the performance sensor, after multiplication by vectors that end in performance sensor.
7. Repeat updates of form factors.
8. Repeat multiplication by vectors of a total of ($n^2$) form factors.
9. Update/record energy and time of arrival at the performance sensor, after multiplication by vectors that end in performance sensor.
10. Plot energy response graph.
11. Sum energy for time intervals of interest.
12. Compute parameters based on relations between energy at different time intervals.

## 4.3. OPTIMIZATION FUNCTIONS

Optimization in this system will be the optimization of form factors based on changes made by effectors. Each effector can be changed based on an objective function, the form factors can be updated, new vectors of form factors can be computed, and the propagation cycle can be repeated.

The objective function of a form factor between two components can be based on three terms, the area, the distance between components and the angle between the components. It will take the form: $f(a, d, \theta)$

Each of the variables in the objective function has a range of values. The ranges are as follows:

1. The area (a) can vary from 0 to ∞.
2. The distance (d) can vary from 0 to ∞, but a practical upper limit is v(initial energy / perception threshold).
3. The angle between components (θ) can vary from 0 to π.

The objective function for a spatial enclosure is a function of a maximum of $(n^2 + n + 1)$ form factors. It will take on the form: $f(ff_1 \ldots\ldots ff_{n^2+n+1})$. An objective function used in the optimization of environmental performance criteria can have up to $(n^2 + n + 1)$ terms. This is a large number of terms in an objective function. However, these terms can be grouped into four sets that behave in a concerted way. These four sets are:

1. Term associated with direct transfer of energy from source to receiver.
2. Terms associated with transfer of energy from a source to all other effectors.
3. Terms associated with transfer of energy from an effector to all other effectors.
4. Terms associated with the transfer of energy from all effectors to the receiver.

## 4.4. COMMON FRAMEWORK

The complex process of optimizing the various environmental performance criteria can be resolved by adopting a common framework for the spatial propagation of the various types of energy. One such framework is the general model of radiation (Mahalingam, 2000). Radiation is simply considered as the transfer of energy between spatially separated surfaces. For the modelling of temperature variation in a spatial enclosure, this technique can be applied directly. The radiosity-based modelling of light propagation in spatial enclosures provides a theoretical framework for modelling illumination levels in the spatial enclosure based on radiation. The radiation-based modelling of sound propagation provides a theoretical framework for the modelling of sound intensity levels in the spatial enclosure (Mahalingam, 1999).

The triple integral form of the radiation equation, that measures radiation from a source to a surface, integrates intensities based the variation of the surface orientation (the cosine or Lambertian component), the area of the surface, the solid angle subtended by the surface at the source, and time. This may provide the common framework that may simplify the optimization process.

This relationship is given by:

$Q_e = \iiint L_e \cos\theta \, dA \, d\Omega \, dt$ (Woan, 2000)

$Q_e$ = energy at a surface

$L_e$ = rate of transfer of energy per unit area per steradian

$\cos\theta$ = angle between surface where energy is being measured and the source

A = area of surface where energy is being measured

$\Omega$ = solid angle in steradians subtended by surface where energy is being measured

t = time in seconds

## 5. Conclusion

This paper has introduced a model for the optimization of environmental performance criteria in spatial enclosures using a system of effectors (sensor-actuator pairs). This model uses a common radiation-based propagation framework for different kinds of energy, namely thermal, luminous and acoustical energy. The effectors that regulate the various environmental performance criteria are shown to form optimization networks or *optimatons*. These *optimatons* behave in a manner that is similar to other well-known computational networks such as neural networks.

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