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SENSOR NETWORK OPTIMIZATION FOR STRUCTURAL HEALTH MONITORING

by
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AN ABSTRACT OF THE THESIS OF

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Sensor placement for physical fault detection on convex plane surfaces is a quick spreading technology that has been used in evolving industrial firms for structural health monitoring purposes. A set of sensors is allocated on the surface understudy and ultrasonic guided waves are excited between sensor pairs to detect and allocate possible damage. The cost of installation and maintenance of such structural health monitoring systems has been reported to grow exponentially as the size of the structure increases. Hence, several techniques for optimizing sensor networks have been presented in literature to improve coverage and fault detection while reducing the number of sensors needed and hence reducing cost. In this paper, a demonstration of the preceding sensor network optimization approaches is presented and an advanced geometrical optimization approach for fault detection and sensor placement is proposed. The approach is formulated as a Mixed Integer Non-Linear program (MINLP) with user defined parameters to simulate actual geometrical conditions of the surface understudy and sensor coverage characteristics. The model is tested in several real case studies with different scenarios of coverage levels for both symmetrical and optimized sensor arrays and assures the efficiency and strong performance of the aforementioned approach. Data fusion is also carried out for the optimal sensor locations determined by the experimentation scenarios and the results confirm the paper findings.

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CHAPTER I

INTRODUCTION

Complex engineering systems like buildings, bridges, aircrafts and many others constitute the basis of our everyday economy. Manuals of codes and standards have been compiled for numerous regions to ensure the safety of these facilities and their serviceability. Nevertheless, design codes and methodologies have not been sufficient to prevent the deterioration or damage of engineered facilities and products upon exposure to severe environmental conditions. Recent seismic activities have revealed the real vulnerability of these civil structures to damage during catastrophes like earthquakes. Having these risks taken into consideration, engineering communities have pushed further to innovate and implement proactive sensing technologies that aim to rapidly detect the onset of structural damage in instrumented structural systems using analytical methods. Hence, the process of estimating the state of structural health by combining damage detection algorithms with structural monitoring systems is called the structural health monitoring process (SHM). [1] In general, SHM is a mimic of the human nervous system by which a group of sensors act together as one sensing network to detect and localize faults within a surface or a body. It is a continuous process that aims to detect anything from ambient vibrations, wind and live loadings on the structure to large scale vibrations, earthquakes and severe damages or local structural failures.[2] SHM systems are widely used in monitoring cracks in concrete, strain and pressure sensing, detection of seismic activity and crash investigations.

Nevertheless, conventional SHM systems installed in tall buildings have been reported in literature to cost excess of 5000$ per sensing channel.[3] This means these systems costs grow at rates faster than regular linear rates upon increase in structure size. A tradeoff exists between SHM feasibility and SHM system costs. For instance, a decent SHM system for a bridge can cost more than $8 million (USD).[4] On the other hand, small numbers of sensors can barely detect structural damage, the fact that provoked sensor network optimization. In this paper, previous sensor network optimization approaches are demonstrated and an advanced optimization approach for sensor networks is proposed.

CHAPTER II

LITERATURE REVIEW

Several optimization approaches have been demonstrated in the field of SHM. Many scholars have focused on determining the minimum number of sensors required to achieve full plate coverage without the need of sensor allocation. Others have developed algorithms that follow an information based approach that depends on the experimental conditions of each sensor. Genetic algorithms and less advanced geometric approaches have also been presented in previous work. The demonstration of the various optimization approaches in literature is summarized in this section.

A. Iterative Optimization

Iterative Optimization is also known as the “trial and error” optimization approach. The process starts with a fixed number of sensors distributed over the entire network then evolves by removing a single sensor at a time and assessing the new coverage. An opposite approach for the iterative optimization method starts by finding the optimal 1-sensor patterns over the plate surface and evolves by adding sensors and evaluating the optimal coverage in each case. In some experiments, for instance, the analysis starts by having 20 sensor locations distributed over the plate. Afterwards, one sensor is removed and the remaining 19 sensors are left with 20 possibilities. The 20 sensor locations are tested and the 19th sensor distribution having the best fitness measure is selected. The sensor location that was not selected is permanently deleted and a similar assessment is carried out for the following sensor distribution. This has proven to be a more cost effective method that results in a lower number of sensors and lower probability of error. Evaluation of the effectiveness of the iterative optimization approach is defined by a measure of fitness. This fitness measure can be considered the normalized mean square error (MSE) between the desired network responses and the initial network training responses. *K. Worden* in his experiments on iterative optimization incorporates two factors into the fitness measure and evaluates fitness based on a scoring method. For instance, a sensor distribution to be considered optimal, had to have the lowest score resulting from the sum of the average MSE and the Maximum MSE for each sensor network distribution. The justification is that having two factors defined in the fitness measure makes it less subject to local minima problems.[5] Successful patterns demonstrate lowest average error and lowest maximum error and no misclassifications.

B. Combinatorial Optimization: Information-Based Approach

Combinatorial optimization is usually expressed in forms of Quadratic Non-linear programs such as the travelling salesman problem. A traditional information-based approach for a sensor placement problem places sensors near the anti-nodes of the low frequency vibration modes of the system. The distribution of sensors is assessed in terms of the covariance matrix [C]. The covariance matrix is the inverse of the Fisher information matrix [F]. Usually, minimizing [C] maximizes [F] and the outcome is the determinant of matrix [F]. Sensors location process is guided by an FE model and the sensors are located according to their Average Driving Point Residue. Sensors with the highest ADPR are selected and contribute to high mode shapes.[6]

A second approach is the Guyan model reduction where master sensor locations are selected by the algorithm and are deleted until the required number of sensors is reached. The objective function is related to the degrees of freedom of the master nodes and their moments of inertia. Both methods illustrated earlier can be either assessed with the modal assurance criterion (MAC) or the condition number of the mode shape matrix that measure the extent of linear dependence between mode shape vectors. The MAC method produces two objective functions. The first objective function Z1 the sum of the off-diagonal elements and Z2 that contains weighting factors for amplification of the desired modes.[5] Sequential deleting of the sensors leaves the sensors producing highest off diagonal matrix.

A third information-based approach for the sensor optimization problem is the Effective independence (EI). It is based EI distribution vector E. The optimization process is iterative, terms in E are sorted and the least important sensor is deleted and the determinant of the Fisher information matrix is maintained.[7]

C. Genetic Algorithms

Genetic algorithms are optimization algorithms that work by encoding the sets of possible parameters in a solution space as a gene. Usually, genes are represented as binary strings ex: 01001001 each gene represents a case of sensor allocation pattern in which the 0 describes absence of sensor allocated and 1 its presence. The optimization starts by randomly generating a set of possible solution genes and selects the fittest genes based on a predefined fitness function usually the inverse of the probability of misclassification. Then it evolves in a Darwinian manner by which the genes selected in the earlier phase are crossed over to produce the next generation of genes. Crossing over occurs by selecting a specific position along a gene pair and switching of the following substrings. Afterwards, the fitness of the genes is compared against the sum of fitness of all genes of the population. The higher the fitness factor the higher the probability of selection. Genes with very high fitness scores are probably to be selected several times for mating and thus are isolated initially from mating and kept for advanced crossover stages in order to guarantee optimal sensor allocation solutions with high objective functions in a process called elitism, a good demonstration of elitism is presented in (Lars Junghans, Nicholas Darde, 2015).[8] On the other hand, new genes can also be introduced to prevent the population from stagnating. The process of mating continues until few elite genes dominate the population. Genetic algorithms have been used a lot in previous work and tend to produce realistic results when compared to other optimization approaches as demonstrated in (K. Worden, A.P. Burrows, 2000).[5]

A good demonstration of the GA approach work mechanism is presented in *Shiyuan Jin's* paper in which a population of genes is defined along with crossover and mutation rates. The population of 80 sensors undergoes crossing over to produce 800 new generations and the fittest genes are sorted out according to a predefined fitness function that focuses on minimizing the communication distance between sensors after dividing the plate into numerous clusters.[9] This approach has demonstrated good coverage results yet seems to utilize high number of sensors in order to minimize the transmission distance and energy loss, the fact that makes it an expensive approach as demonstrated in (Celebi, 2002).[3]

D. Simulated Annealing

Most sensor network optimization techniques tend to move downwards with the objective function in an attempt to reduce the number of sensors needed; therefore, there is a great possibility that the optimization converges to a local minimum. Optimization with Simulated Annealing (SA) is very similar to the concept of metal annealing by which a metal is heated and left to cool down and tends to increase and decrease the objective function instead of strictly decreasing it to avoid local minima. A good example of optimization via SA is presented in (A.A. Kannan et al, 2005) [10] in which the optimization starts with a fixed number of 200 nodes and a cost function is defined as the difference between the anticipated distance (usually the transmission distance) and actual distance between an anchor node and a non-anchor node . More than 200 nodes are randomly spread out at first and SA evolves by shifting the locations of non-anchor nodes while maintaining a distance equal to the transmission distance between sensors and with a probability of 80% of accepting a bad uphill move if needed. Iterations are carried out for sets of nodes to attain equilibrium for each and minimal cost function. The advantage of this approach is that it outperforms the regular GA approaches and is capable of achieving global solutions for complex objective functions. For instance, SA can deal with n- sensors and achieve optimality levels of 99.5% correct classification (K. Worden, A.P. Burrows, 2000).[5] Nevertheless, this approach is very time consuming and needs numerous iterations to achieve global optimality. A good demonstration of the performance of GA along and a hybrid algorithm mix between GA and SA is presented in (Lars Junghans, Nicholas Darde, 2015)[8] that demonstrates that GA alone may not achieve global optimality and proposes a new hybrid algorithm that highlights the importance of using SA in thermal building optimization problems.

E. Mixed Integer Non-linear Programming (MINLP)

The sensor network optimization problem is formulated as a mixed integer non-linear program (MINLP) having quadratic constraints. MINLP problem constraints are characterized by having continuous and discrete variables simultaneously along with non-linear functions. Applications of MINLP problems exist in a wide range of fields including OR, Chemical engineering, finance etc.

The general form of MINLP is as following:

Min $\boldsymbol{f}(\boldsymbol{x}, \boldsymbol{y})$

$\boldsymbol{St}$:

$\mathbf{c}_{\boldsymbol{i}}(\mathbf{x}, \mathbf{y}) = \mathbf{0} \qquad \forall\, \boldsymbol{i} \in \boldsymbol{E}$

$\mathbf{c}_{\boldsymbol{i}}(\mathbf{x}, \mathbf{y}) < \mathbf{0} \qquad \forall\, \boldsymbol{i} \in \boldsymbol{I}$

$\boldsymbol{x} \in \boldsymbol{X}$

$\boldsymbol{y} \in \boldsymbol{Y}$ Integer

Each $\mathrm{c}_i(\mathrm{x}, \mathrm{y})$ is a mapping from R^n to R, and E and I are index sets for equality and inequality constraints, respectively. Typically, the functions f and c_i have some smoothness properties, i.e., once or twice continuously differentiable.[11] Additional details on MINLP and other types of optimization problems can be found at the NEOS online guide. NEOS is an online free internet-based service for solving numerical optimization problems by the help of a rich variety of state of the art optimization solvers. In general, MINLP problems are difficult to solve since they combine the difficulties of both Mixed Integer programming and Nonlinear Programing.

CHAPTER III

PROPOSED OPTIMIZATION APPROACH

In this section, an advanced MINLP geometric approach for the sensor network placement optimization problem is studied based on optimizing the distance between the sensor path and the control points understudy. The approach is not only formulated but also modeled as a mixed integer non-linear program via AMPL. Additional information concerning mixed integer non-linear program with quadratic constraints, AMPL software and the problem formulation itself are presented in the subsections that follow.

A. Problem Formulation

Several approaches for sensor network optimization discussed in literature have been demonstrated earlier in this paper, however there are other geometric approaches presented in literature for determining the level of coverage in a sensor network and aim to provide a tool for sensor network assessment and not optimization. A good example of the geometric approach in literature is presented in (Chi-Fu Huang, Yu-Chee Tseng, 2005).[12] The authors in this paper allocate sensors randomly and assume that the covering parameter of each sensor is a circular disk of a given radius "r" according to its coverage range. Then the assessment proceeds by defining the areas and points that fall within one or more transmission parameter of sensors and classifies their coverage into levels accordingly. This method was translated into a computerized interface that is capable of highlighting the coverage characteristics of the various areas of the plate by identifying the redundancy of coverage parameters of various sensors but does not seem to identify the exact location of sensors to achieve optimal coverage nor the ability to manipulate the problem parameters such as the minimum number of sensors needed and the designated coverage levels. Thus this method is classified as a method of sensor network assessment rather than optimization. In this paper, the problem of sensor network placement for SHM is formulated as a MINLP with an objective function of maximizing coverage while being constrained by the number of sensors available, the plates' dimensions and geometry, the coverage range of each sensor path and other geometrical constraints that are demonstrated in details below.

1. Parameters

- K: Set of Control points
- (x_k, y_k): Coordinates of control point $k, k \in K$
- N: Set of sensors to be placed
- M: A large number
- τ_{ijk}: Positive random variable between 0 and 1
- $dimx \geq 0$ $dimension\ of\ Plate\ in\ X\ direction$
- $dimy \geq 0$ $dimension\ of\ Plate\ in\ Y\ direction$

2. Decision Variables

- $C_k = \begin{cases} 0\ if\ control\ point\ k\ is\ not\ covered \\ 1\ otherwise \end{cases}, k \in K$

- (x_i, y_i): Coordinates of sensor $i, i \in N$
- $C_{ijk} = \begin{cases} 0\ if\ control\ point\ k\ is\ not\ covered\ by\ sensor\ line\ (i,j) \\ 1\ otherwise \end{cases}, i \in N, j \in N, k \in K,\ i < j$
- d_{ij} = Distance between sensor i and sensor j, $i, j \in N, i < j$
- d_{ijk} = Distance between sensor line (i,j) and sensor $k, i \in N, j \in N, k \in K, i < j$
- d_{ik} = Distance between sensor i and control point $k, i \in N, k \in K$

3. Formulation Model

$$\max \sum_{k \in N} C_k$$

$subject\ to$:

$$d_{ij}^2 = \left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 \ \forall\ i \in N, j \in N, i < j \tag{1}$$

$$d_{ik}^2 = (x_i - x_k)^2 + (y_i - y_k)^2 \ \forall\ i \in N, k \in K \tag{2}$$

$$d_{ijk} \leq 1 + M\left(1 - C_{ijk}\right) \qquad \forall i \in N, j \in N, k \in K, i < j \tag{3}$$

$$\left(\textstyle\sum_{i \in N} \sum_{j \in N: i < j} C_{ijk} \geq\ C_k\right)\ \forall\ k \in K, i < j \tag{4}$$

$$d_{ijk}^2 \geq \left(\tau_{ijk}x_i + \left(1-\tau_{ijk}\right)x_j - x_k\right)^2 + \left(\tau_{ijk}y_i + \left(1-\tau_{ijk}\right)y_j - y_k\right)^2 \quad (5)$$

$$i, j \in N, k \in K, i < j$$

$$d_{ik} - d_{ij} = a_{ijk}^+ - a_{ijk}^- \quad i \in N, j \in N, k \in K, i < j \quad (6)$$

$$d_{jk} - d_{ij} = b_{ijk}^+ - b_{ijk}^- \quad i \in N, j \in N, k \in K, i < j \quad (7)$$

$$a_{ijk}^+ \leq M\left(1 - C_{ijk}\right) \; i \in N, j \in N, k \in K, i < j \quad (8)$$

$$b_{ijk}^+ \leq M\left(1 - C_{ijk}\right) \; i \in N, j \in N, k \in K, i < j \quad (9)$$

$$-\sum_{i\in N}\sum_{j\in N: i<j} C_{ijk} + 2 \leq 2(1 - C_k) \; \forall\, k \in K, i < j \quad (10)$$

$$\sum_{j\in N: i<j} C_{ijk} \leq 1 \quad \forall i \in N,\; k \in K, i < j \quad (11)$$

$$\sum_{i\in N: i<j} C_{ijk} \leq 1 \quad \forall j \in N,\; k \in K, i < j \quad (12)$$

$$x_i \leq dimx \quad (13)$$

$$y_i \leq dimy \quad (14)$$

$d_{ij}, d_{ijk}, d_{ik}, \tau_{ijk}, a^{+}_{ijk}, a^{-}_{ijk}, b^{+}_{ijk}, b^{-}_{ijk}\ dimx, dimy$ >0

C_{ijk}, C_k Binary Variables

The first two equations in the optimization approach aim to calculate the distance between sensors i and j and the distance between sensor i and control point k respectively according to the typical distance equation between two points. In equation 3, for a specific control point k to be covered, the distance between the sensor path and this control point d_{ijk} must be less than 1 unit which is considered to be the coverage distance of all sensor paths in this problem. This parameter is a user defined attribute which can be altered as needed to fulfill the problem requirements. Equation 5 serves to calculate the distance between the sensor path ij and the control point k. Equations 6, 7, 8 and 9 represent the triangular inequality equations between a sensor pair and a control point. These equations ensure that the control points covered fall within the sensor pair path and not at the extension of this path. Equation 10 is one of the most significant equations of the model and aims to define the level of coverage required to solve the problem. Currently this equation is for level 2 coverage by which 2 sensor paths are required for the equation to hold and can be user defined to any coverage level needed at the expense of longer computational time. Equations 11 and 12 have demonstrated the ability to improve the performance of the model. These equations state that the summation of sensor path for a given sensor and a given control point to all other sensors should not exceed 1 path. This prevents the code from overlapping sensors and covering a control point by two lines passing through the same sensor. Equations 13 and 14 are also user defined attributes for the aim of defining the plates' dimensions.

As mentioned earlier, it is possible to classify coverage into levels according to the number of sensor pair paths providing coverage to every control point. In this approach, the control point is not considered to be covered unless the required coverage level is achieved. Level-1 coverage is considered to be the first step of sensor placement optimization problems and aims to recognize the presence or absence of material deformation along the available sensor pair paths. Level-2 coverage is also known as localization coverage that permits fault localization by locating the possible material deformation through the intersection of 2 or more guided waves near each control point. Level-3 coverage used for "Evaluation" since this level evaluates the severity of the localized damage by providing improved coverage of 3 or more sensor pair path to every control point and hence is considered to be a more accurate method. Huang and Tseng state that accurate localization of damage requires coverage of three sensor paths, according to triangulation protocols (Chi-Fu Huang, Yu-Chee Tseng, 2005). [12] In this paper, level "n" will be referred to the case of coverage by "n" sensor pair paths.

After identifying the nature of the problem and formulating it, prolonged search and testing of convenient solvers capable of solving non-linear and non-convex problems suggested that the Basic Open Source Non-linear Mixed Integer Programming Solver (Bonmin) was one of the most efficient solvers for this type of problems and has been used in literature thoroughly in dealing with this type of problems.[13] Bonmin is a hybrid solver for mixed integer non-linear programming based on an outer-approximation-based branch-and-cut-based algorithm and a pure branch-and-bound algorithm. Bonmin defines a node search tree and branches on its variables solving for feasible and optimal solutions.[14] It implements six different algorithms in solving MINLPs including branch and bound, an outer approximation based decomposition algorithm, an outer approximation based branch and bound algorithm and a hybrid outer approximation for non-linear programming based branch and cut algorithms and other techniques that are highlighted in the Bonmin User Manual.[15] Additional details regarding the non-linear branch and bound approach and its different types can be found in (Belotti, P. et al, 2013).[16] Problems to be solved with Bonmin can be coded in AMPL; a computer based language used for solving large scale optimization problems and is capable of incorporating and supporting a wide range of solvers. The software offers an interactive interface that facilitates model building for users of different optimization background. Detailed description of the design and implementation of AMPL is provided in (Robert Fourer et al, 1990) .[17] In general, there is no universal global optimizer for MINLP problems. These problems have demonstrated lack of performance efficiency and insufficient numerical robustness and a good example is highlighted in (Ausen, 2012).[18] However, four major key factors have been implemented in our optimization approach to ensure the optimality and robustness of our proposed solution.

First of all, the sensor network optimization problem is known to be complex and computationally demanding since there exist an infinite number of points along the x and y axis to be assessed. The initial approach to the problem was to relax the coverage of the sensor path $\boldsymbol{Cijk}$ and solve for sensor locations, then to feed the preliminary results of the relaxed problem as an initial solution to the actual problem, hence requiring less computational time for solving. The plate understudy was divided into a definite set of control points in order to boost the computational efficiency of the solver by reducing the processing time required. The actual coverage of these control points provided by the proposed optimization approach was assessed on a separate code after each run with higher number of control points to validate the robustness of the results. It was observed that the optimizer had provided consistent optimization results for various sensor network problems. Another key factor for enhancing the model’s robustness is integrated within the solver itself. In dealing with MINLP, Bonmin offers two options within the branch and bound tree at root and at node for solving the root node or each node of the tree, respectively, with a user-specified number of different randomly-chosen starting points, saving the best solution found. Bonmin provides the option of allowing continuous branching even if the solution value to the current node is worse than the best-known solution, hence exploring the entire feasible region and all possible solutions of the problem, the fact that overcomes the local optimality dilemma in regular optimization approaches.

CHAPTER IV

SIMULATION CASES

A. Simulation Cases Studied

After modeling the problem as a MINLP via AMPL several cases were studied as listed below.

1. List of Simulation Cases

- Optimizing a sensor network on a square 10x10 units^2 plate
- Optimizing a sensor network on a circular plate of diameter 10 units
- Optimizing a sensor network level 2 on a triangular plate of side 10 units
- Optimizing a sensor network level 3 on a triangular plate of side 10 units
- Optimizing a sensor network with 20mm coverage
- Optimizing a sensor network with increased control points

The aim behind the optimization of sensor networks on Square, Circular and Triangular plates in the first three sets of experiments is twofold. First of all, it is necessary to demonstrate how the optimization code will allocate the sensor network along various geometric shapes having different boundaries. Second, it is essential to study how the optimization behavior varies as the pattern of the control point distribution changes.

Moreover, level 3 optimization cases are also studied to highlight the effect of increasing the number of intersecting sensor pair paths on the coverage of the plate itself and hence improving fault localization chances. It is also essential to study the change in the optimization behavior when higher coverage levels are required with low number of sensors available. Coverage of a sensor path was taken to be 40mm from each side of the path as demonstrated in earlier SHM work in literature.[19] However, the case of 20 mm coverage for each sensor path is also considered to demonstrate the flexibility in choosing the sensor types and the effect of each on the optimization process as the required number of sensors to achieve complete coverage differs. The case of adding control points to the plate understudy is also considered in order to demonstrate how increasing the control points in a selected area of the plate increases the coverage of this area. In addition to studying the effect on the computational time for processing the problem and on the precision of coverage provided by the sensor locations determined. A detailed summary of the scenarios coded and the optimization results is illustrated in the section below. In general the most important aim of these sets of experiments was to understand and validate how the optimization process outperforms the normal and symmetric distributions of the un-optimized sensor sets.

B. Optimization for Square Plates

In the aim of evaluation of the performance of optimized sensor networks, a comparison of the coverage of both symmetric and optimized sensor networks was carried out on a square plate 400x400 mm. In normal cases the average coverage of the piezoelectric sensor pair path is considered to be 40 mm from each side of the path in an elliptic manner. In an attempt to simulate the dimensions and coverage of our problem, a scaled code was prepared. The dimensions of the plate were scaled down to 10x10 units and the coverage of the sensor pair path was also scaled to 1 unit. Control points were allocated 2 units away from the boundary of the plate and coverage was assessed on the base of being covered by two sensor pairs (level 2). An initial assessment for level "2" coverage was carried out by placing 8 symmetric sensor pairs on a 10x10 square plate and evaluating control points coverage as shown in Figure 1. This initial assignment was then compared to an optimized one. The case of 8 sensors was simulated and the optimized sensor locations were determined as shown in Figure 2. The strong symmetric distribution of the 8-sensor array gives full plate coverage of all control points similar to the optimized sensor network that was tested and produced equivalent optimal coverage with different sensor locations. Accordingly, it can be noted that multiple optimal solutions exist for large number of sensors and that the optimized sensor network is not completely random but has a unique symmetry of its own similar to the symmetric distribution across the plate edges. Therefore it is recommended to reduce the number of sensors used.

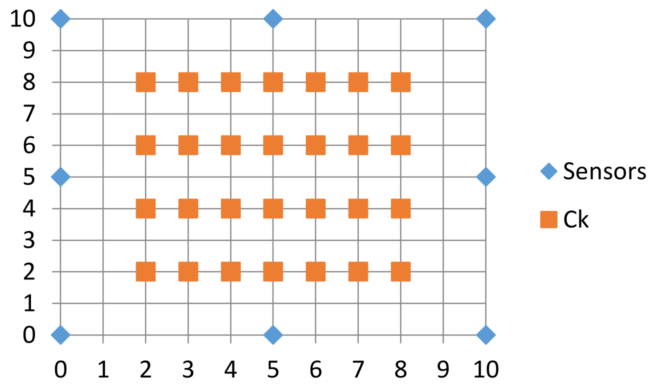

Figure 1: 8-Sensor Symmetric Network-Square Plate

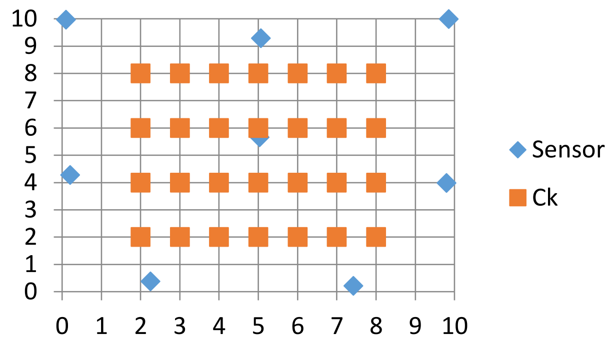

Figure 2: 5-Sensor Optimized Network-Square Plate

A quick assessment of the plate coverage showed that seven and six sensors gave full plate coverage as well; hence, the number of sensors was reduced to five to be able to better understand how the optimization deals with the insufficiency of sensors and optimizes the plate coverage level. The details of both the symmetric and optimized sensor networks are shown in Figures 3 and 4 respectively.

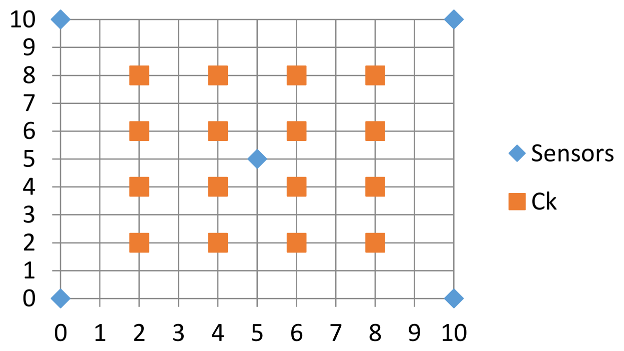

Figure 3: 5-Sensor Symmetric Network-Square Plate

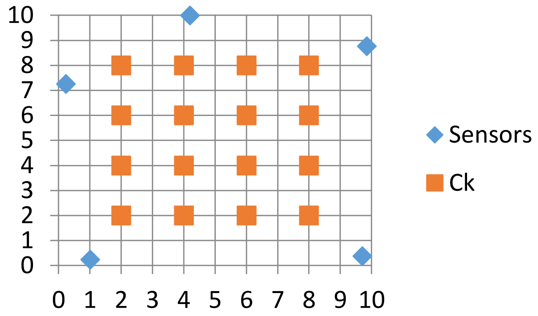

Figure 4: 5-Sensor Optimized Network-Square Plate

After assessing coverage for both plates, it is shown that the optimized set of sensors provides improved coverage to the plates' control points covering 75% control points when compared to the initial set of symmetric sensors that was able to cover 50% of the plate. The approach of optimization used in solving the sensor allocation problem is to branch and bound the problem in numerous iterations experimenting on various solution branches until a global optimal is reached. Therefore, it can be concluded that five sensors are not enough to cover all control points of the square plate but optimization will improve the overall coverage of the plate when compared to a regular symmetric allocation.

C. Optimization for Triangular Plates

Optimization for triangular sensor networks is an important process for structural health monitoring since most irregular shapes can be divided into triangular shapes. Optimization of triangular sensor networks produces high quality results in half the computational time required for square and rectangular shaped plates due to their geometric nature. Eric B. Flynn. Michael D. Todd, 2010 have developed a genetic algorithm that is able to optimize the sensor placement process and is able to allocate sensors on plates of various shapes and dimensions based on the distribution of Bayes risk of sensor networks as a fitness function and assigning penalties to false alarms and missed detections.[20] The algorithm also incorporates sensor characteristics and surrounding network noise and is considered to be a top performer reaching 99.8% optimality levels. In their approach, Eric and Michael experiment on a right isosceles triangular plate of 125 cm side dimension and study how their algorithm is able to determine the location of 8 piezoelectric sensors to obtain optimal locations for full plate coverage. In our study, a comparison is undertaken to evaluate how our code performs against Eric and Michael's algorithm for sensor network optimization on a triangular plate having to scale-dimensions and similar geometric characteristics while using the same number of sensors. The results are presented below.

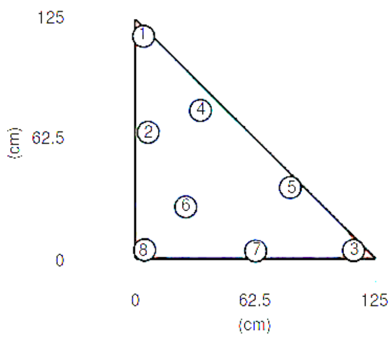

Figure 5: Michael and Eric Genetic Algorithm Optimized 8-Sensor Network

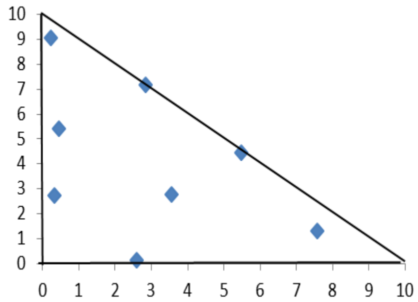

Figure 6: Advanced Geometric Approach Optimized 8-Sensor Network

The previous figures show the sensor locations based on the Bayes risk genetic algorithm approach Figure 5 compared to our optimization method results in Figure 6. Testing demonstrates that both optimization methods achieve full plate coverage and tend to allocate the majority of the sensors near the peripherals of the plate. It is also noted that only one sensor is allocated at the inside in both cases the fact that validates our approach in sensor network optimization. Another set of optimization experiments has been conducted on a right isosceles triangle with side dimensions of 10x10 units representing a 40x40 cm triangular plate. The dimensions and coverage have been scaled to the actual plate size tested that was cut diagonally in half to produce two identical triangles. The modeling code has been modified by adding the following equation: $x_i + y_i <= 10$ (15)

Such that x_i and y_i represent the coordinates of the sensors to be allocated.

18 control points have been assigned on the surface of the triangle understudy and both initial and optimized solutions of eight sensors were enough to achieve full plate

coverage. Therefore, the number of sensors was reduced to five sensors in order to evaluate how the optimization will cope with this sensor deficiency. The results of the experiments are shown hereunder.

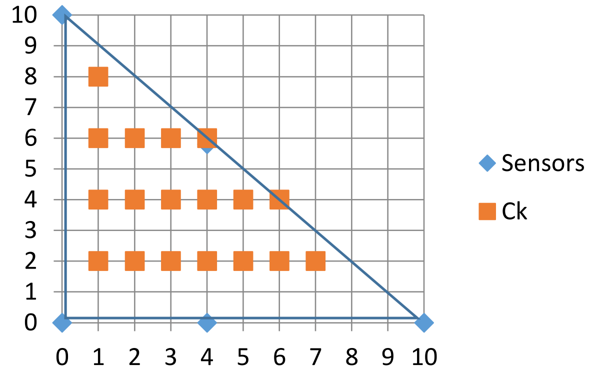

Figure 7: Initial 5-Sensor Network Triangular Plate

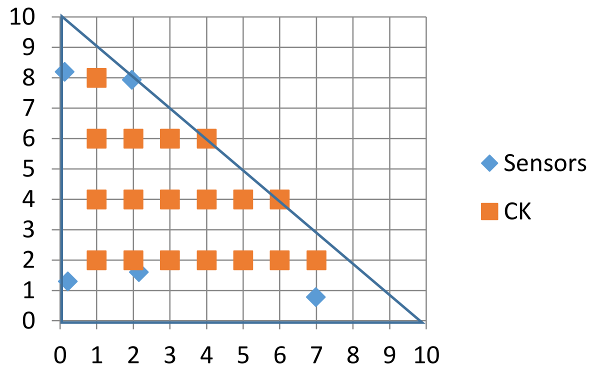

Figure 8: Optimized 5-Sensor Network-Triangular Plate

A strong initial solution of 5 sensors set at the corners of the plate yields a fair coverage of 60% yet is not sufficient to achieve acceptable SHM levels. On the other hand, the use of the optimization code allocates the 5-sensor network in a scientific manner that achieves a high coverage level of 90%. This proves that as the number of sensors becomes scarce and the decision of allocation becomes more critical, the output of the optimization code becomes more valuable by outperforming the regular allocation process. A good example that facilitates the role of the optimization process is that for a small number of control points a primitive solution of 3 sensors allocated on the corners of a triangle produces 10% coverage whereas a much stronger solution of 70% is achieved by the optimization code. The fact that demonstrates that for a given level of coverage, a smaller optimized sensor network can be produced, hence reducing the overall cost of the structural health monitoring process.

D. Sensor Network Optimization for Circular Plates

In this section, the effect of sensor network optimization is studied on circular plates having a radius of 5 units. The code has been modified by adding the following equation

$$(x_i - 5)^2 + (y_i - 5)^2 \leq 25 \tag{16}$$

Such that x_i and y_i represent the coordinates of the sensors to be allocated. This equation represents the boundary of the circular plate understudy and forces the code to allocate sensors within this boundary. The comparison between random and optimized sensor allocation is demonstrated in Figures 9 and 10 respectively.

In this comparison it was shown that both sensor networks were able to achieve complete level 2-coverage of the selected control points on the plate. It was also noted that the random allocation by engineering sense and the optimization both had similar sensor network distribution within the circumference of the plate. Therefore, the number of sensors in this study was reduced to 5 along with 12 control points to be able to identify the effect of sensor insufficiency on the performance of the optimization.

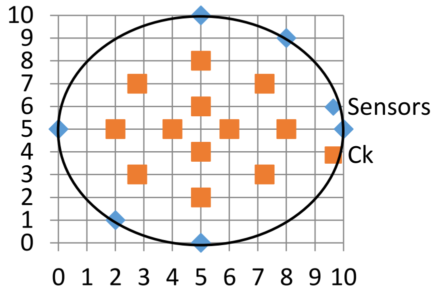

Figure 9: Initial 6-Sensor Network-Circular Plate

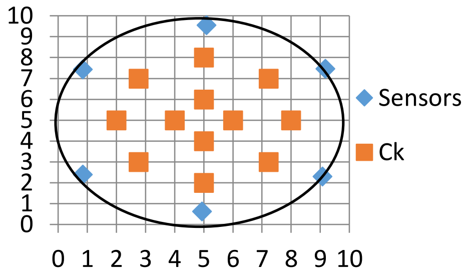

Figure 10: Optimized 6-Sensor Network

By using common engineering sense 5 sensors were allocated at the major centerlines of the circular plate along with 1 central sensor inside. The sensor network was able to achieve coverage of 67%. On the other hand, the optimized sensor network was able to outperform the normal sensor distribution by achieving coverage of 92%, both distributions are shown in the figures below:

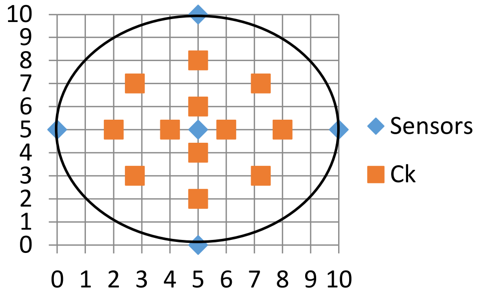

Figure 11: Initial 5-Sensor Network-Circular Plate

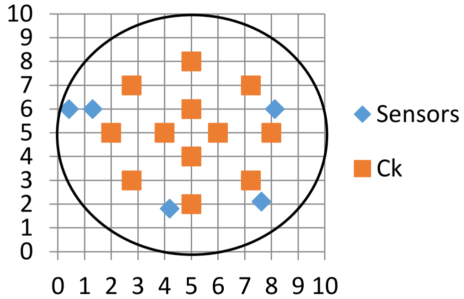

Figure 12: Optimized 5-Sensor Network-Circular Plate

It is concluded that the optimized sensor network produces higher coverage rates than the random sensor network allocated. Another interesting remark was observed is that when the number of sensors decreases the optimization code tends to allocate two sensors close to each other, the purpose of this allocation is to achieve level 2 coverage for the maximum number of points possible. Hence it can be concluded that the optimization prefers quality coverage of small number of control points rather than poor coverage to a greater amount of points. This conclusion is best demonstrated in the relaxed version of the problem where the optimization is allowed to bypass this constraint and the sensors are allocated freely, it is noticed that the optimization will deploy the sensors in a sparse manner providing poor quality coverage to a wider area as concluded earlier the fact that explains the optimization behavior.

E. Optimization for Level 3 Coverage

Previous work in the field of sensor network placement focused on the assessment of coverage of various surface areas. Good work has been done to come up with genetic algorithms that could improve and assess coverage in polynomial time yet none seems to scientifically prove the number of sensors required for complete plate coverage nor the exact sensor locations. In this paper, advanced research has been done to identify the minimum number of sensors required for coverage, the exact locations of sensors to be deployed to maximize coverage and most importantly to be able to localize faults in triangular plates. In general, *C. Huang and Y. Tseng* demonstrate in their work that the accurate localization of faults requires level 3-coverage, in other words, control points should be covered by 3 or more sensor pair paths in order to correctly localize damage according to triangulation protocols.[12] In our approach, localization coverage (level 3) can be reached by setting the coverage parameter to 3. As mentioned earlier, the level of coverage in the sensor network optimization model is a user defined attribute that can be manipulated to achieve higher levels of coverage at the cost of longer computational time. This method provides improved coverage and fault detection accuracy to the plate understudy. For the sake of demonstration, optimization of a level 3 sensor network for a triangular plate was studied. The code was altered by changing equation 10 as follows:

$$-\sum_{i\in N}\sum_{j\in N:i<j} C_{ijk} + 3 \leq 3(1 - C_k)\ \forall\, k \in K, i < j \qquad \text{(10-a)}$$

Experimentation has been performed on the previous triangular plate to verify the number and location of sensors required, testing starts with 4 sensors and 10 control points were selected. It is found that **70%** localization is achieved for the optimized locations of sensors when compared against the random allocation that covers 20% only of the selected control points. One sensor is then added to the experiment and the code is run again to achieve global localization. The results of level 3-coverage for both types of sensor networks are shown in the figures below:

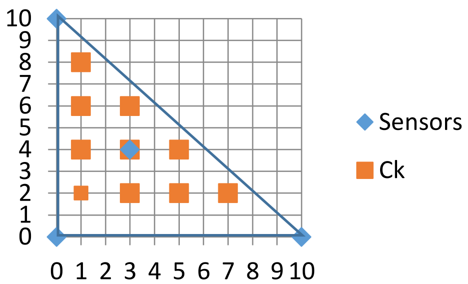

Figure 13: Initial 4-Sensor Network-Level 3 Triangular Plate

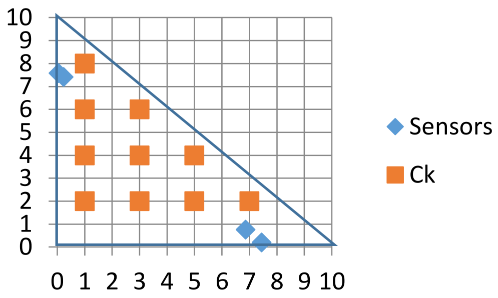

Figure 14: Optimized 4-Sensor Network-Level 3 Triangular Plate

It is noticed that the 4 sensors were allocated symmetrically along a line passing through the center of the triangular plate. Increasing the number of sensors to 5 produces 80% level 3-coverage for the optimized allocation compared to the regular and random allocation that produces only 40% level 3-coverage for the selected control points. The distribution and localization results are shown in the figures below:

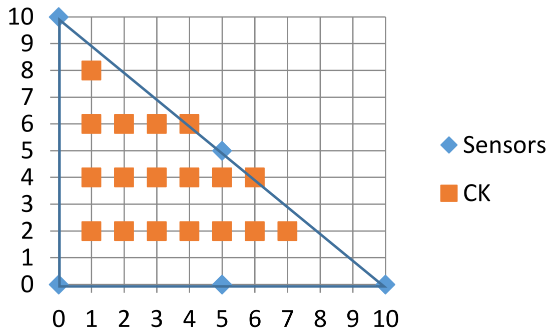

Figure 15: Initial 5-Sensor Network Level 3-Triangular Plate

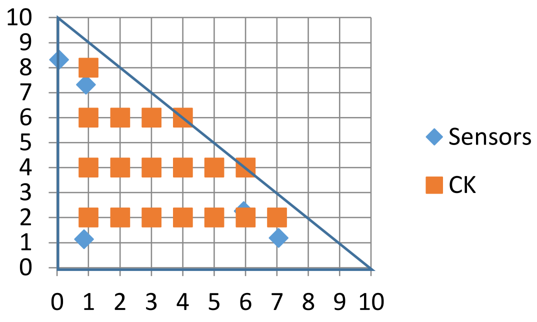

Figure 16: Optimized 5-Sensor Network-Level 3 Triangular Plate

Hence it is clear that the optimized 5-sensor array is enough to achieve level 3 coverage for all the selected control points of the plate. In this experiment, the optimization behavior becomes more complex and the optimization tends to place sensors in symmetry with the plate's center and in pairs in order to achieve level 3 coverage for specific control points rather than to disperse the sensors throughout the plate area.

CHAPTER V

DATA FUSION

Data fusion of sensor networks is the process of aggregation of the coverage generated by every sensor pair path along the plate surface. Data fusion is carried out for the optimized sensor locations in order to assess the levels of coverage at the selected control points. The assessment was conducted along with proper normalization of coverage to the area of interest. The data fusion results are shown below.

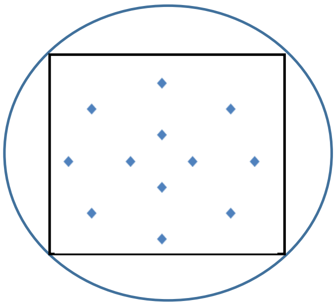

Figure 17: Circular Plate-Area of Coverage Assessment

A. Square Plate

As shown earlier, 6 sensors are enough to provide level 2-coverage to the square plate understudy. Data fusion carried out for square plates of 8, 7 and 6 sensors confirms our previous findings. Data fusion of an insufficient number of sensors such as 5 sensors demonstrates how the optimized allocation outperforms the regular sensor network allocation. The results of the data fusion are shown in the figures below.

The paths used for image reconstruction are also visualized to provide a better understanding of how coverage is being provided in terms of sensor pair paths. Figure 18 represents the paths used for image construction using 8 sensors while Figure 19 represents the data fusion of the preceding sensor pair paths. It can be noted that the optimized sensor locations have a unique distribution throughout the plate with highest concentration in the plate center due to the nature of the damage detection and allocation problem that requires the distribution of the sensors around the peripherals of the plate in order to ensure maximum coverage levels to the control points inside. This phenomenon is noticed in Figure 19 in which the data fusion highlights this high coverage level with a yellowish orange color close to the plate center. The reduction of number of sensors to 7 and 6 sensors respectively will gradually start to reduce the coverage concentration from the center of the plate and will generate a uniform coverage to the maximum area possible while maintaining the minimum coverage level required to all control points.

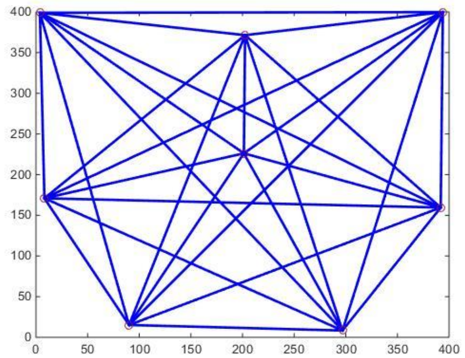

Figure 18: Paths Used for Image Construction-8 Sensors

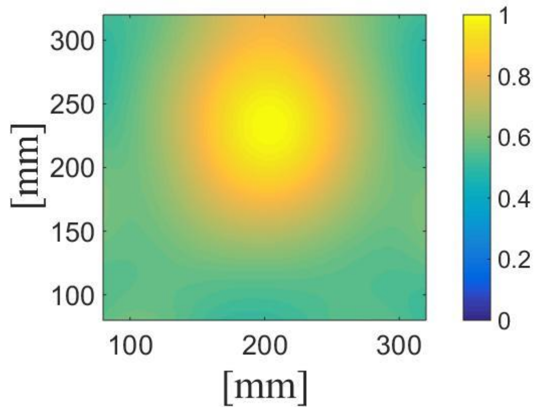

Figure 19: Data Fusion-8 Sensors

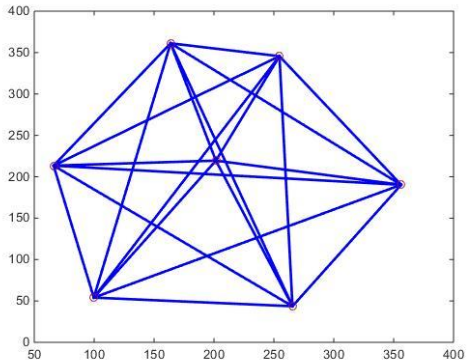

Figure 20: Paths Used for Image Construction-7 Sensors

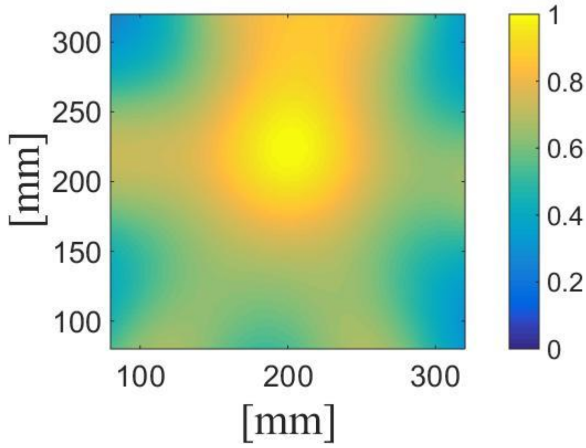

Figure 21: Data Fusion-7 Sensors

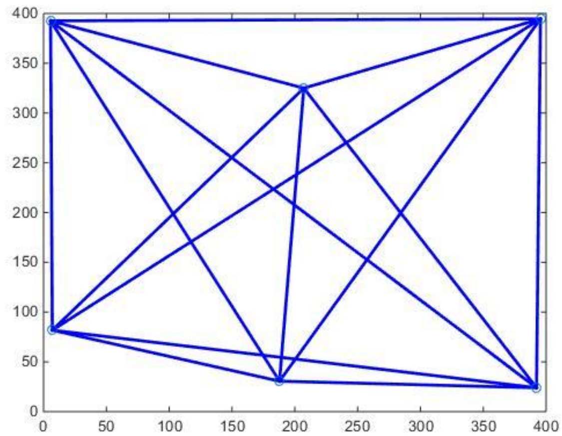

Figure 22: Paths Used for Image Construction-6 Sensors

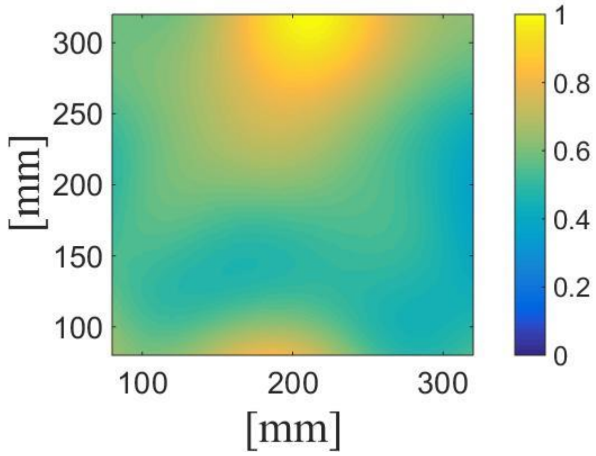

Figure 23: Data Fusion-6 Sensors

Further reduction to the number of sensors utilized will require the optimization to take critical decisions in terms of determining the optimal number of control points covered while making use of the insufficient number of sensors. A comparison between the random and optimized allocation in terms of data fusion and coverage is provided in the figures below for a 5 sensor network.

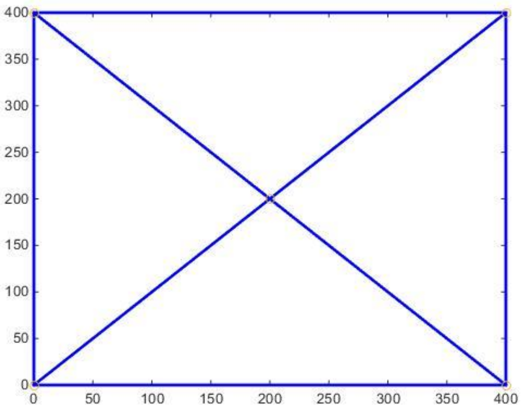

Figure 24: Paths Used for Image Construction-5 Sensors Random Allocation

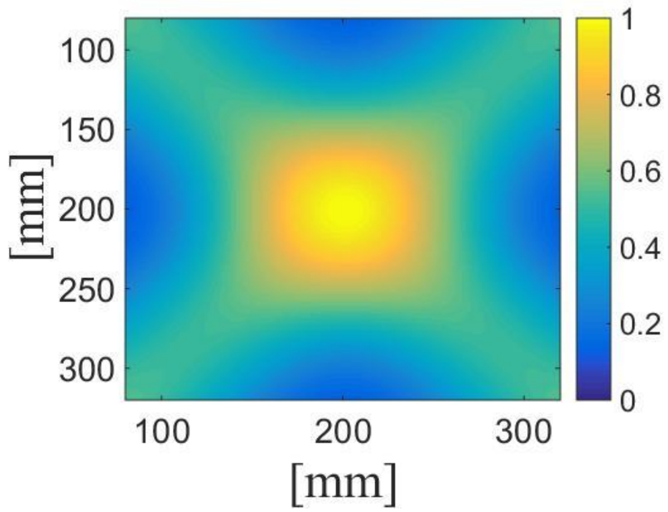

Figure 25: Data Fusion-5 Sensors Random Allocation

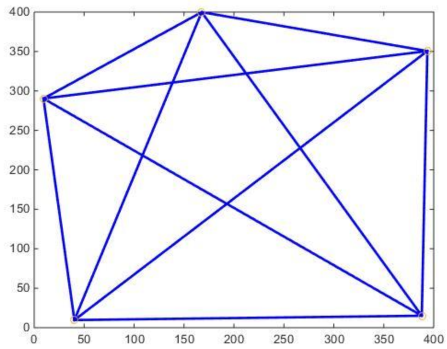

Figure 26: Paths Used for Image Construction-5 Sensors Optimized Allocation

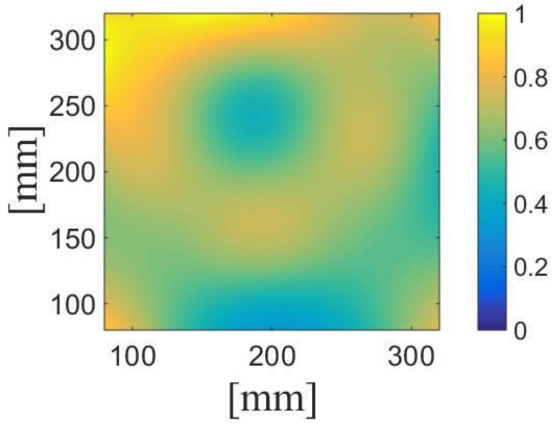

Figure 27: Data Fusion-5 Sensors Optimized Allocation

It is noticed that the optimized allocation of 5 sensors provides better coverage with increased uniformity than the random sensors network allocation that has demonstrated the existence of coverage dead zones at the peripherals of the square plate represented in dark blue color.

B. Circular Plate

The optimization of sensor networks on a circular plate was also considered. Six sensors were determined analytically to provide full coverage to the control points understudy. This number was then reduced to 5 in order to carry out a comparison between the random and optimized allocation. The performance of the model and the efficiency of the proposed approach are demonstrated in terms of extended coverage provided to all control points while having minimal dead zones. The sensor pair paths and the data fusion figures of both random and optimized cases are represented below.

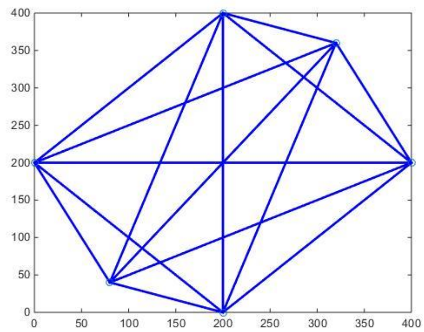

Figure 28: Paths Used for Image Construction-6 Sensors Random Allocation

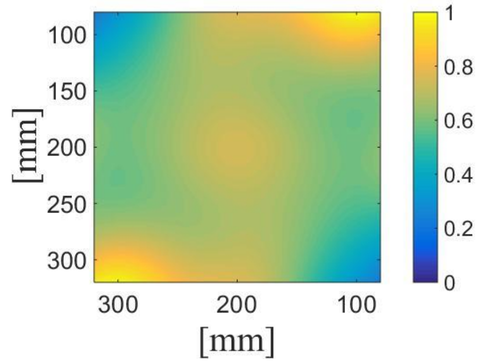

Figure 29: Data Fusion-6 Sensors Random Allocation

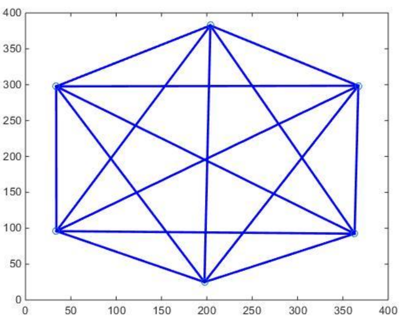

Figure 30: Paths Used for Image Construction-6 Sensors Optimized Allocation

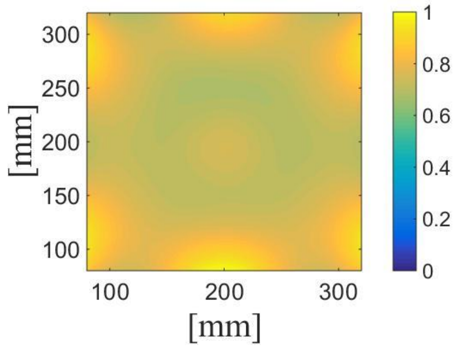

Figure 31: Data Fusion-6 Sensors Optimized Allocation

It can be noted that for the same number of sensors and for complete control point's coverage, the optimized allocation provides a more uniform and distributed coverage throughout the circular plate, unlike the random allocation that tends to leave some corner areas with lower coverage levels than other areas. The reduction of sensors to 5 highlights the vast difference between the efficiency of the optimized allocation when compared to the random allocation. The comparison is represented in the following figures.

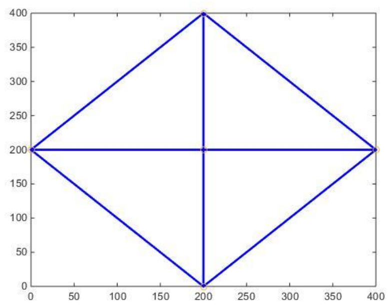

Figure 32: Paths Used for Image Construction-5 Sensors Random Allocation

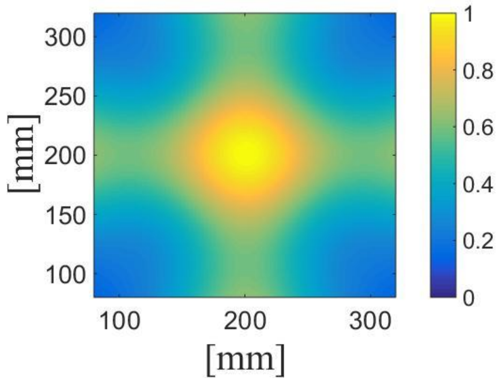

Figure 33: Data Fusion-5 Sensors Random Allocation

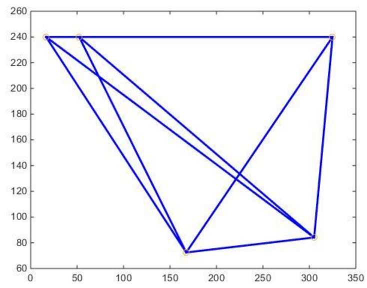

Figure 34: Paths Used for Image Construction-5 Sensors Optimized Allocation

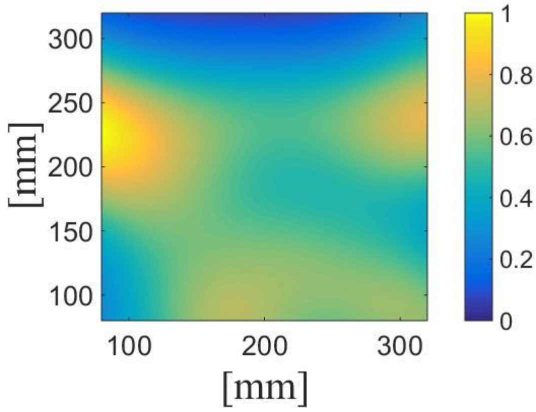

Figure 35: Data Fusion-5 Sensors Optimized Allocation

Optimization allocates new coordinates for the 5 sensors utilized and does not refer to the previous optimization of 6 sensors. Hence optimization of the sensor network is studied independently to provide the best scenario for each case by itself. Data fusion of both optimized and random allocation demonstrates the improved coverage provided by the optimized sensor set..

C. Triangular Plate

It has been demonstrated in the previous sections that the level 2-optimization of the sensor networks using the advanced geometric approach has outperformed the regular and random allocation of sensors by providing improved coverage and reduced dead zones to the plate understudy. Another scenario worth studying is the effect of setting the coverage parameter to level 3 towards the sensor network behavior and coverage. Therefore, a comparison is presented between triangular plates having optimized sensor networks of levels 2 and 3 respectively.

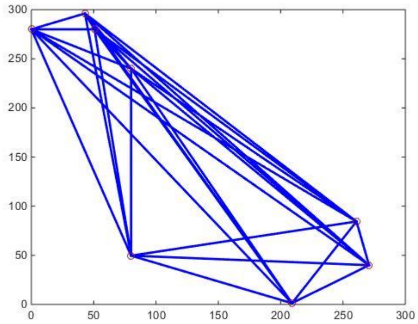

Figure 36: Paths Used for Image Construction-8 Sensors Level 2 Optimized Allocations

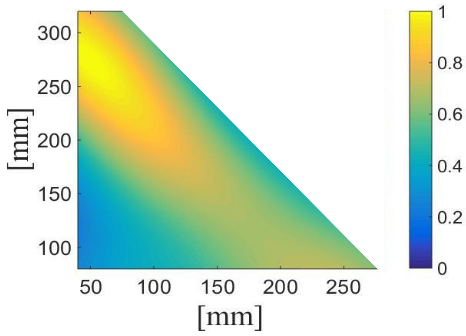

Figure 37: Data Fusion-8 Sensors Level 2 Optimized Allocations

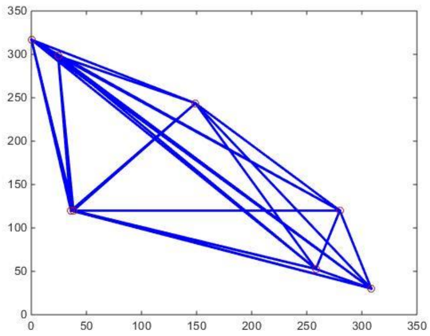

Figure 38: Paths Used for Image Construction-8 Sensors Level 3 Optimized Allocations

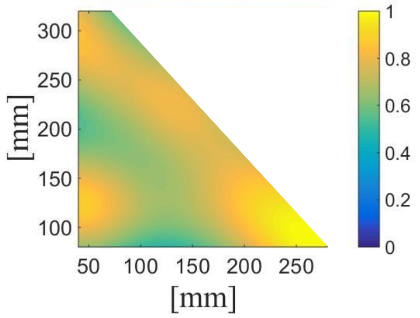

Figure 39: Data Fusion-8 Sensors Level 3 Optimized Allocations

For the same number of sensors, the optimization problem is solved differently. The optimization with level 3 coverage provides coverage with 3 sensor pair path. This fact makes the sensor network optimization problem more complex and computationally demanding as the problem solving time will increase exponentially with the increase in this parameter. Nevertheless, it is clear that for the same number of sensors the coverage provided by the level 3 optimization model provide uniform and improved coverage to the entire plate including the corners. Therefore, the number of sensors was reduced to 5 and the assessment was repeated.

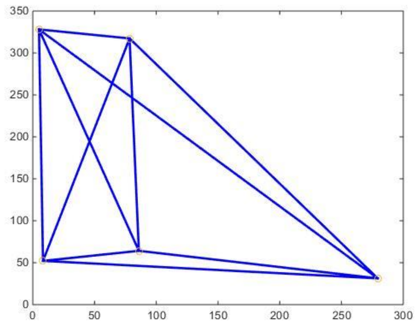

Figure 40: Paths Used for Image Construction-5 Sensors Level 2 Optimized Allocations

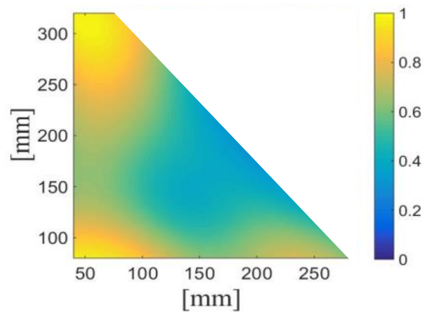

Figure 41: Data Fusion-5 Sensors Level 2 Optimized Allocations

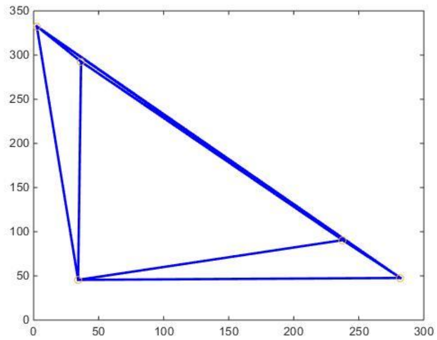

Figure 42: Paths Used for Image Construction-5 Sensors Level 3 Optimized Allocations

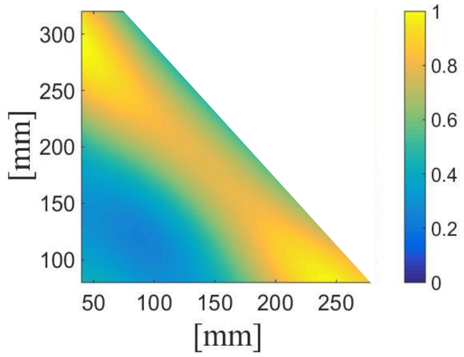

Figure 43: Data Fusion-5 Sensors Level 3 Optimized Allocations

The comparison between levels 2 and 3 optimization of the 5-sensor network highlights major remarks. The first remark is that 5 sensors is the minimum number of sensors required to provide control point coverage in both cases due to the strong contrast in the coverage levels within the same plate and at specific areas as revealed by normalization. Another important remark is that the optimization prefers quality coverage of control points rather than poor coverage of the entire plate as demonstrated in the data fusion of level 3 sensor locations.

D. 20mm Coverage

The coverage of the sensor pair path was reduced to 20 mm from each side, which is equivalent to half unit coverage for the scaled optimization model and the case of optimizing the sensor network on a triangular plate is studied. As demonstrated earlier, 6 sensors were needed to achieve full plate coverage of level 2. In the following sets of experiments, a triangular plate having 6 sensors with 20 mm coverage is studied and the number of sensors is afterwards increased and coverage is re-assessed until full plate coverage is achieved. The aim behind these sets of experiments is to be able to demonstrate the flexibility in integration of the problem parameters including the sensor pair path coverage characteristics in addition to highlighting how the behavior of the optimizer varies as the coverage distance becomes less.

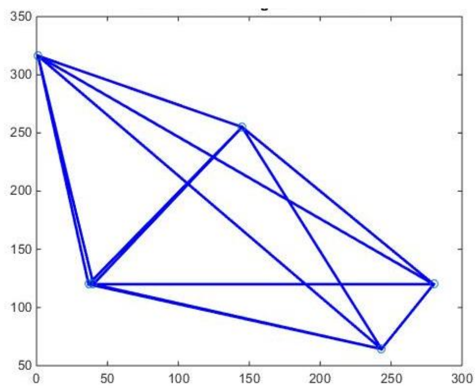

Figure 44: Paths Used for Image Reconstruction 6 Sensors 40mm Coverage

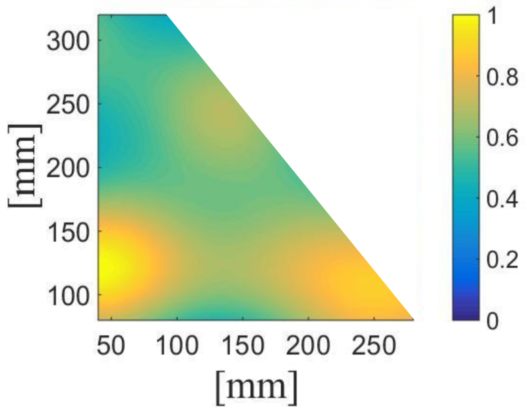

Figure 45: Data Fusion of 6 Sensor Network with 40mm Coverage

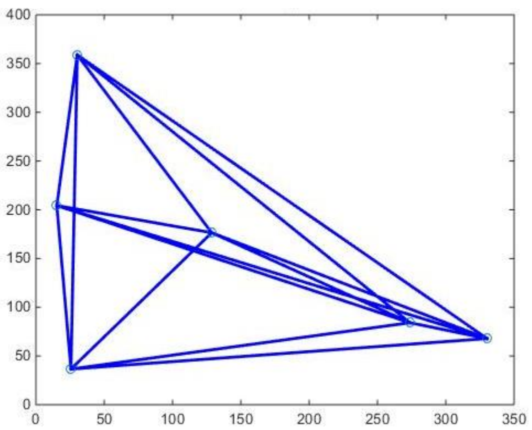

Figure 46: Paths Used for Image Reconstruction 6 Sensors 20mm Coverage

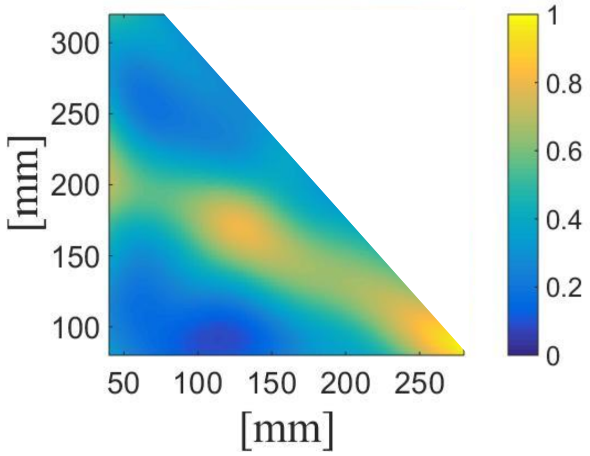

Figure 47: Data Fusion of 6 Sensor Network with 20mm Coverage

The use of 6 sensors provides full coverage to the triangular plate with 40 mm coverage of sensor path but provides only 50% coverage of the plate for the case of 20mm coverage. If the correlation between the number of sensors and coverage provided is linear, 12 sensors with 20mm coverage are needed to provide full plate coverage again. Hence the number of sensors is increased to 7 sensors and the results are shown below.

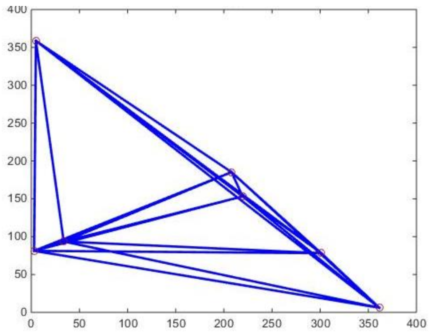

Figure 48: Paths Used for Image Reconstruction 7 Sensors 20mm Coverage

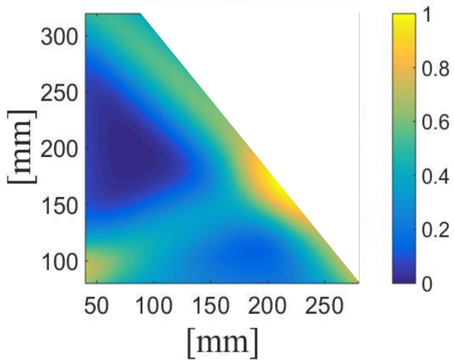

Figure 49: Data Fusion of 7 Sensor Network with 20mm Coverage

The assessment of coverage for a 7 sensor network with 20 mm coverage of sensor paths demonstrates that the plate is 80% covered with having a dead zone represented in dark blue. Hence additional sensors are needed for the experiment. The use of 8 sensor network along with the optimization results are demonstrated in the figures below.

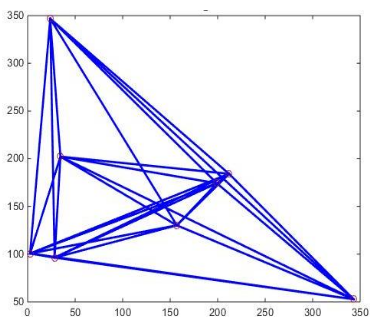

Figure 50: Paths Used for Image Reconstruction 8 Sensors 20mm Coverage

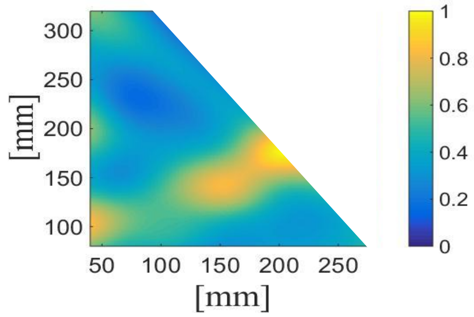

Figure 51: Data Fusion of 8 Sensor Network with 20mm Coverage

The use of an 8-sensor network for the triangular plate produces 100% level 2-coverage. Nevertheless, it is clear that the coverage demonstrated by the data fusion figures of both the 20mm and 40 mm sensor networks demonstrates that a higher level coverage with improved uniformity is provided by the 40mm sensor network. This is fairly justified by the increased aggregation of sensor pair path covering larger areas despite the allocation and number of sensors used in each problem. The advantage of the optimization algorithm is that it acts as a sensor reduction tool providing efficient coverage with lower number of sensors.

E. Additional Control Points

The advanced geometric approach assumes that the plate is divided into a specific number of control points user defined initially. The level 2 optimization for instance focuses on maximizing the number of control points covered by 2 pairs of sensor paths. In this section, the same triangular plate is studied twice before and after increasing the number of control points and the effect is translated in terms of the new sensor locations and improved coverage. The first experiment is carried out on a triangular plate with 7 sensors and 10 control points for level 2 coverage as shown in the figure below.

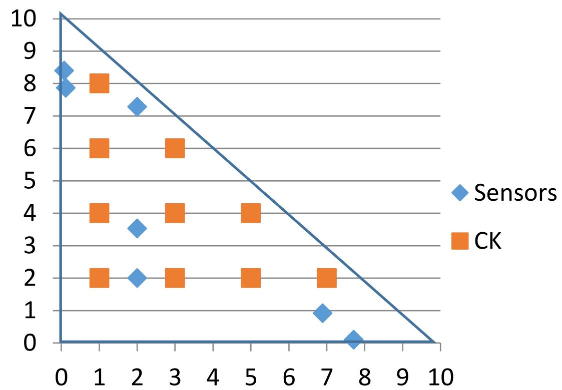

Figure 52: 10Ck Optimized 7-Sensor Network

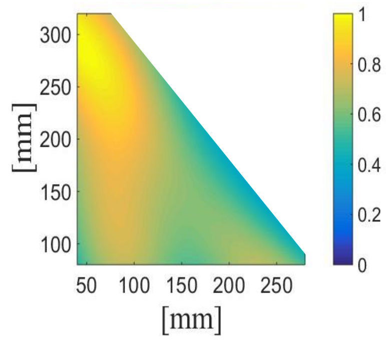

Figure 53: 10Ck Optimized 7-Sensor Network Data Fusion

The sensor network optimization is then carried out for the same triangular plate with 16 control points distributed in a uniform manner and the results are represented below.

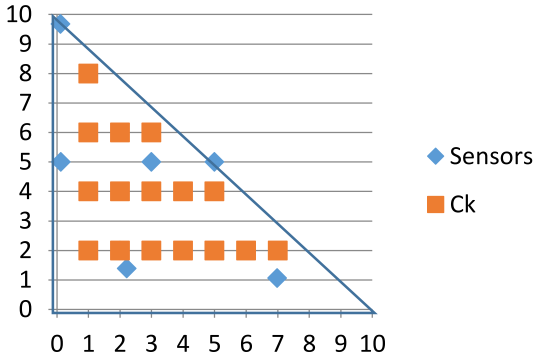

Figure 54: 16Ck Optimized 7-Sensor Network

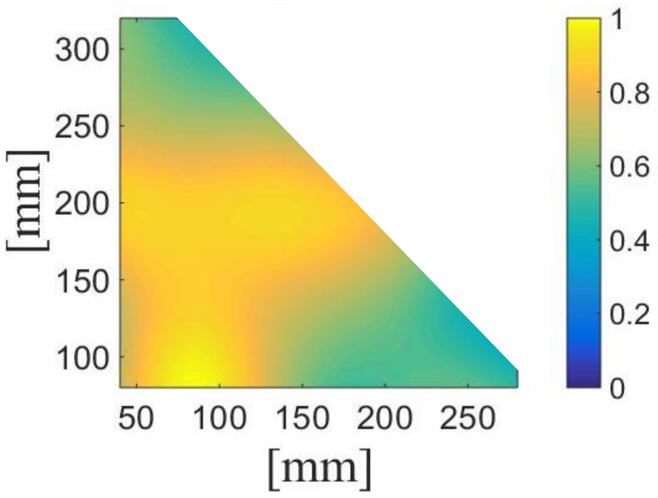

Figure 55: 16Ck Optimized 7-Sensor Network Data Fusion

It is noticed that both cases demonstrate full plate coverage with higher coverage levels concentrated in the middle in the case of additional control points. It is also noted that the computational time has increased for solving the optimization problem.

Another experiment is carried out to analyze the optimization behavior upon increasing the number of control points of a level 3 8 sensor network. Similar to the previous cases, the optimization begins with a 10 control point network which evolves into a 16 control point network and the results are demonstrated in the figures below.

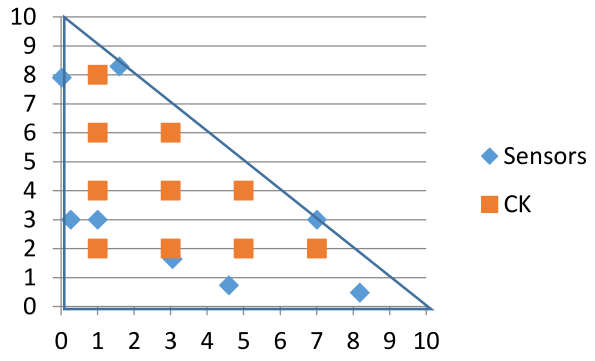

Figure 56: 10Ck Optimized Level 3 8S Network

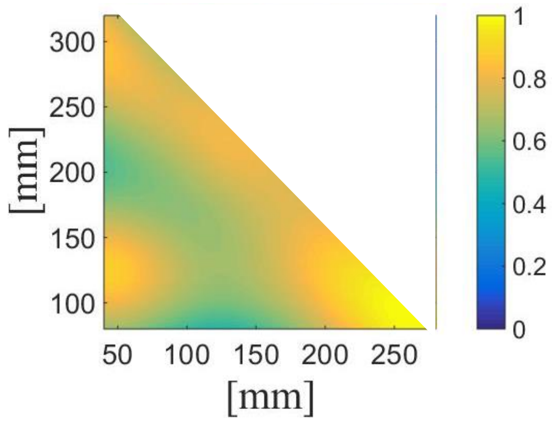

Figure 57: 10Ck Level 3 Optimized 8S Network Data Fusion

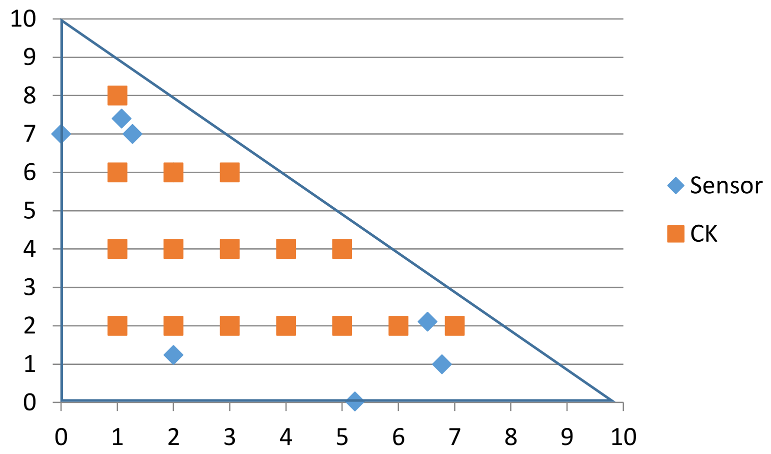

Figure 58: 16Ck Optimized Level 3 8S Network

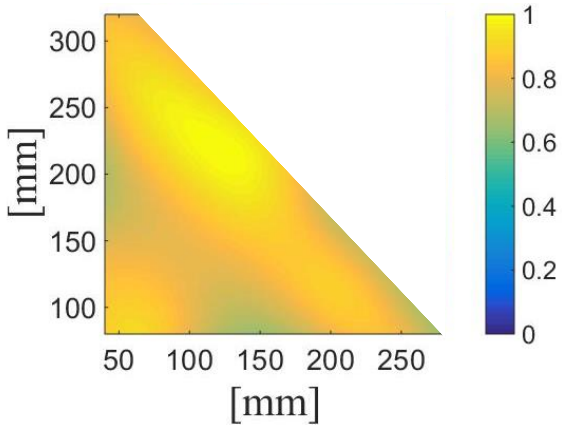

Figure 59: 16Ck Level 3 Optimized 8S Network Data Fusion

Increasing the number of control points to 16 instead of 10 has generated new sensor locations along the triangular plate. The new sensor locations when tested have demonstrated improved coverage with increased uniformity. Nevertheless, both cases have demonstrated full plate coverage. Therefore, increasing the number of control points is a user defined attribute that is capable of producing better coverage with higher uniformity levels along the plate. However this option has also demonstrated increased computational time and effort.

F. Discussion

After presenting the proposed optimization algorithm for sensor network placement, the algorithm was tested on several cases. The first set of experiments was conducted on plates with varying geometry such as Square, Circular and Triangular having predefined control points. The control points were selected in a manner simulating the geometry of the plate understudy. The first observation was that as the number of control points increases the computational time for solving the optimization problem increases exponentially. The triangular shaped sensor networks were optimized faster than the square and circular plates due to their non-symmetric geometry and fewer control points. Data fusion was carried out to evaluate the actual coverage produced by the optimized sensor locations after aggregation of the coverage produced by each sensor pair path. Coverage was defined by the number of intersecting sensor pair path at every control point. For instance, level 3 coverage required the overlap of the coverage area produced by 3 independent sensor pair path. The first assessment was conducted on a square plate with 16 control points. The optimization was time demanding and several optimal results were found covering all control points due to the symmetric geometry of the problem. Since 8 sensors were enough to achieve full coverage of the preselected control points, the number of sensors was reduced gradually to 5 until it was insufficient to produce full coverage. The optimization was conducted on 5 sensors and better coverage was produced using the optimization algorithm. Similar work was conducted on the circular plate and on the triangular plate. Validation of the proposed algorithm was experimented on a triangular plate with 8 sensors against an existing top performer for sensor network optimization and both algorithms converged to global optimality using 8 sensors only with very similar distribution. Nevertheless, coverage levels were defined and level 3 coverage was experimented on triangular plates and the results demonstrated that additional sensors were needed to achieve level 3 coverage especially for the control points along the peripheral of the plate. Control points at the center of the plate were naturally covered by several sensor pair paths due to the spider web structure of the sensor locations that demonstrated highest overlap levels at the center. For adequate number of sensors, level 3 coverage was achieved and data fusion results produced demonstrated clear uniformity between the coverage of the control points throughout the plate. Lower number of sensors used left areas of the plate uncovered while having areas completely covered the fact that described the algorithm behavior focusing on quality coverage of smaller areas rather than poor coverage of larger areas. Additional experimentation on the behavior of the sensor network optimization algorithm confirmed that the optimization tends to determine new positions of sensors used in the sensor networks when subject to any change in one of the formulation parameters such as the coverage distance, coverage levels, number of sensors and number of control points studied. For instance, the sensor locations determined for an 8-Sensor network are completely different and independent of the optimized sensor locations for a 7-Sensor network. Networks with same number of sensors and same number of control points produced different sensors locations when optimized for coverage of levels 2 and 3 respectively. Furthermore, the optimization behavior was tested with sensors having 20 mm coverage instead of 40 mm and the results demonstrated that new sensors locations were determined for the same number of sensors and control points used. Even though it additional sensors were needed in the 20 mm cases to achieve equivalent coverage to the 40mm sensors networks however the number of additional sensors needed was reduced to more than half indicating the efficiency of the optimizer . The case of adding control points was also studied for triangular sensor networks and the optimization behavior was highlighted. It was shown that new sensor locations were determined along the triangular plate understudy when the number of control points was increased. The new sensor locations when tested have demonstrated improved coverage with increased uniformity keeping in mind that both cases have demonstrated full plate coverage. It was concluded that increasing the number of control points, which can be categorized as one of the user defined attributes, is capable of producing better coverage with higher uniformity levels along the plate. The key contribution of this user defined attribute is that it provides a tool to achieve higher coverage and improved uniformity levels to specific and critical areas of the plate understudy. However, this option has also demonstrated increased computational time required for solving the optimization problem and thus it is to be used with limitations in the number of control points to be analyzed. The results demonstrated in each optimization experiment cannot be labeled as the global optimal results of the problem since there exist multiple optimal solutions to the infinite sensor locations along the x and y axis in addition to the nature of the non-linear optimization problem. Nevertheless, several measures were followed to guarantee the robustness of the optimization results as mentioned earlier.

CHAPTER VI

CONCLUSION

An advanced optimization method for sensor network placement has been presented in this paper. The research has introduced a non-linear geometric approach capable of assessing and optimizing sensor network efficiency in terms of improving coverage level; number of sensors needed and fault localization. The main approaches for sensor network optimization presented in literature have also been demonstrated in this paper. Iterative optimization has proven to be preliminary and time consuming providing results that are dependent on the previous optimization stages of n+ 1 sensors. Genetic algorithms are also strong approaches that outperform the regular iterative approaches and are able to cope with the optimization problem of sensor allocation; however, GA's have demonstrated long computational time and near optimal results yet many problems converged to local minima due to the nature of these algorithms that strictly allow one directional motion of the objective function. The Simulated Annealing approach has also been discussed briefly in this paper and tends to give global optimal results for optimization problems in general since this method allows the objective function to take steps in both upwards and downward directions even after convergence in order to determine the global optimal solution of the problem. This makes the solutions of the SA approach very trustworthy and reliable. Nevertheless, the approach we propose has been capable of: assessing and optimizing sensor network efficiency in terms of improving coverage level; number of sensors needed and fault localization. The optimization algorithm is also capable of eliminating the human interference in the allocation process of sensors by determining the optimal location (Cartesian Coordinates) of sensors utilized as part of the major decision variables of the optimization process. This is unlike most of the previous work done in the SHM field in which the sensors are initially set and sensor network coverage is assessed accordingly. In addition to translating the geometric optimization approach into a digitized algorithm available for users and capable of modeling the problem according to three different types of convex shaped plates and optimizing it. More work in this field is to be done in the near future including enhancing the model performance and computational time required, upgrading the optimization approach to accommodate for non-convex surfaces, maximizing intersecting paths and considering the case of sensor failure.

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