# Development of an Evolutionary Algorithm for Design of Electron Guns for Material Processing

Colin Ribton[1,2] and Wamadeva Balachandran[1]
[1]*College of Engineering Design and Physical Sciences, Brunel University London, West London, U.K.*
[2]*Electron Beam Section, TWI Ltd, Granta Park, Abington, Cambridge, U.K.*

Keywords: Optimisation, Electron, Modelling, Evolution.

Abstract: The design of high quality electron generators is important for a variety of applications including materials processing systems (including welding, cutting and additive manufacture), X-ray tubes for medical, scientific and industrial applications, microscopy, and lithography for integrated circuit manufacture. The many variants of electron gun required, and the increasing demands for highly optimised beam qualities, demands more systematic optimisation methods than offered by trial and error design approaches. This article describes the development of evolutionary algorithms to enable the automatic optimisation of the design of vacuum electron guns. The gun design usually is required to meet specified beam requirements for the applications of interest, so within this work, beam characteristics from the calculated electron trajectories, for example brightness, intensity at focus and beam angle, were derived and used as a measure of the design fitness-for-purpose. Evolutionary parameters were assessed against the efficiency and efficacy of the optimisation process using an analogous design problem. This novel approach offers great potential for producing the next generation of electron guns.

## 1 INTRODUCTION

The design of electron guns is typically carried out with analysis software tools to test whether prospective designs will meet the design requirements. As such, the design of guns is at best an informed trial-and-error process. Using present techniques, the final design settled upon may not be the best available, and may just be a local optimum for the feature and dimension changes attempted. Confidence that the best design has been found can be increased by carrying out further analysis of different designs, but this can be time consuming and ultimately not satisfactory.

Requirements for electron guns are generally specified as beam parameters suitable for the application (ISO 2008). Typically, this would be a required intensity at a certain working distance from the end of the gun column, or a range of required values – but the beam angle may also be important too. For example, lower angles are specified for thick section welding applications so that the beam is intense through the thickness of the weld, whereas for thin section welding the beam angle can be higher, as a more shallow depth of focus can be tolerated. Normally an electron gun will be designed to be suitable for a range of applications, so the beam requirements may be stated as a list of intensity and power at a working distance. The accelerating potential is influential on the beam characteristics but usually this parameter has a fixed maximum for a particular application, constrained by the specification of high voltage components and X-ray shielding. In design optimisation terminology, electron guns have many variables of geometry and electrical operation, and are likely to have multiple objectives in all but the simplest of cases.

The primary challenge addressed by this work is to assess how automated design evolution methodologies can be successfully applied to electron gun designs.

Within this work, techniques have been developed for quantifying the electron optical properties of beams produced by analytical simulations of prospective gun designs. A methodology has been developed to automatically generate electron gun models, which give accurate prediction of electron trajectories. Methods for encoding the design have been developed and tested – potentially allowing a variety of optimisation techniques to be applied.



Ribton, C. and Balachandran, W..
Development of an Evolutionary Algorithm for Design of Electron Guns for Material Processing.
In *Proceedings of the 7th International Joint Conference on Computational Intelligence (IJCCI 2015) - Volume 1: ECTA*, pages 138-148
ISBN: 978-989-758-157-1

The focus of this work was upon an evolutionary method for optimisation of designs to enable automatic design of electron guns to meet specified requirements within defined geometric and electrical constraints. The aim was to develop a method whereby a designer can identify beam requirements and system constraints, which are then used to find an optimum electron gun geometry.

The aims of the work were as follows.

• To investigate the best way of assessing and quantifying the beam quality over the operational range of the gun.

• To develop an optimisation methodology for design of electron guns – in particular the use of an evolutionary design technique that will use the quantified beam characteristics as a quality factor

• To carry out a case study where the methodology will be applied to an electron gun design with the aim of demonstrating the viability of the design process.

# 2 BACKGROUND

## 2.1 Meta-heuristic Optimisation Methods

There are many variants of optimisation techniques that have been applied to engineering design (Sykulski, 2008). Design problems typically may be characterised as having multiple input variables where no assumptions can be made about their relationship to the solution, i.e. the solution function cannot be assumed be of any type, and cannot be assumed to be continuous. In addition, many problems will have local optima. The solution is often found by using computer modelling to simulate the candidate solution, with quantified outputs being derived from the model to assess its suitability. Where no assumptions can be made regarding the solution function, meta-heuristic methods are used. Many of these have been modified to explore the input variables' ranges more widely to avoid being 'trapped' in local optima. Optimisation methods include simulated annealing (Kirkpatrick et al., 1983), particle swarm optimisation (Clerc, 1999) and ant colony optimisation (Dorigo et al., 1999).

Where there are multiple objectives (measures of fitness) it is likely that no one solution will optimise all of these. Consequently, there are a set of optimal solutions that are equally weighted. If a representative sub-set of these is plotted in objective space, a Pareto front is displayed (Hawe and Sykulski, 2007). All solutions on the front are equally optimal and none of them could be improved in one objective without another objective being diminished. Selecting one of the solutions can then only be carried out by applying another measure of fitness, or by a subjective choice.

Evolutionary algorithms (Denies et al., 2013) use processes of selection, mutation and reproduction to attempt to find an optimal design. Variables for the candidate solutions must be encoded in a set of genes. The solutions are analysed, scored according to the design requirements and a sub-set of the best designs is selected. The processes of inheritance, genetic cross-over, and mutation are applied to generate a new population of candidate solutions. Normally, the population is generated initially as a random set of solutions and then with each generation the fittest are selected to parent the next generation. The process continues until a satisfactory solution is generated.

For the reported work evolutionary algorithms were investigated for electron gun design for the first time. The optimisation process can be formally stated as follows. Tentative designs are fully described genetically. The function:

$$f(x)\colon \Phi_g \rightarrow \mathbb{R}$$

assigns real values to genes, see section 3.2, where $\Phi_g$ represents the genotypic search space. The optimal solution $\hat{x}$ is found from

$$\hat{x} = \max_{x \in \Phi_g} f(x)$$

where $f(x)$ is the objective function to be maximised (Franz 2006).

In the case of electron guns this is a non-continuous function with many local maxima. In this work the objective function is derived from electron optical characteristics of the beam produced by the design, and these are calculated by modelling the tentative solution x in finite element software to find field and charge distributions, ray tracing and then electron optical calculation, see section 3.1.

## 2.2 Electron Gun Design

Successful gun design requires calculation of electron emission and the focusing of electron beams that can be achieved as they are accelerated. High voltage and high power electron beams for material processing applications were first demonstrated during the late 1940s and 1950s by Steigerwald in Germany, Stohr in France and Wyman in the USA prior to the availability of computer modelling software.

The higher current beams required new design approaches to avoid beam aberration due to the mutual repulsion of the electrons, particularly as they are first emitted from the cathode. In particular, the Pierce gun geometry was developed that used focusing electrostatic fields to overcome the beam spreading caused by space charge (Pierce, 1954).

As computing power became available, the first electron optical software for the design of guns and optics was developed initially for accelerator experiments – notably at Stanford University in USA (SLAC) (Herrmannsfeldt, 1988) and Rutherford Appleton Laboratories (RAL) (Biddlecombe and Simkin, 1983). Computer analysis of electron gun designs allowed production of higher beam powers. Highlights included developments during the 1970's and 1980's at Steigerwald, Sciaky and TWI.

The design of electron guns, lenses and deflection systems has advanced significantly since the introduction of computer modelling of electrostatic and electromagnetic systems. In particular, development of high power guns used for welding and melting, where space charge plays a significant role in determining the beam qualities, has depended upon accurate modelling. The programs from SLAC and RAL have been developed further in scope and capacity, taking advantage of computer hardware developments, and are now available as EGUN and the Opera software package respectively. There are now many other electron gun analysis programs available. An example of a 2D model solution is given in figure 1. As the model is axisymmetric, only the right half is shown. The cathode is positioned at Z=0 and the beam emerges from the anode at Z=-50. In essence, the software packages take as inputs the geometry, the cathode electron emission characteristics and applied potentials, and produce a set of electron beamlet trajectories. These trajectories can be analysed further to derive electron optical properties of the beam – see section 3.

Mathematical analysis techniques have been applied to optimise the curvature of cathodes in electron guns (Lewis et al., 2004), and these have been shown to be effective. It may be possible to develop further these techniques to look at the combined shape of the gun electrodes and cathode, however the complexity of the problem space, and the number of possible combinations, may extend computing times beyond reasonable durations.

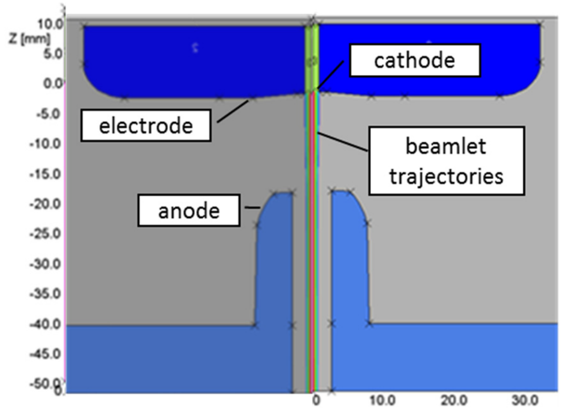


Figure 1: Example of a 2D solution of an electron gun showing the geometry in cross section and the electron beamlet trajectories.

For highly constrained variables, response surface modelling techniques such as kriging (Hawe and Sykulski, 2007), (Lebensztajn et al., 2004) have been deployed. Kriging is a method originally developed for geo-statistical modelling. It has been applied to electromagnetic problems to interpolate between known values in order to find an optimum value – for example to optimise the pole piece profile to produce a required magnetic field distribution.

This approach is most suitable for investigating minor changes to geometry, where the variation is reasonably constrained and where a continuously variable optimisation function is experienced. Evolutionary algorithms, by comparison, are far more flexible in dealing with a more complicated solution space, and far more capable of searching across several local maxima for an optimal solution.

Very recently published work has looked at shape optimisation using evolutionary algorithms for a magnetron injection gun (Jiang et al., 2015). In this work the objective function optimised the electron velocity spread. The reported work differs in using processing beam characteristics for the objective function, which takes into account the electron optics and processing requirements rather than direct use of the output from an electron gun model.

In summary, many different optimization techniques are available. Prior to this work, only kriging has been applied to processing electron gun design, and this in a limited fashion.

# 3 AN OPTIMISATION METHOD FOR ELECTRON GUN DESIGN

## 3.1 Beam Quality Metrics

Any optimisation method will require a quantified measure of the suitability of the design to meet the specified requirements. In the case of electron gun design, it is important therefore to derive beam quality metrics as a gauge for the design fitness. Within this work a space charge solver and electron trajectory plotting software package has been used to analyse designs. It was then necessary to derive the beam characteristics from the electron trajectories from the analysis. These were required to be in a form that could then be gauged against requirements.

It was necessary to analyse any one design over a number of different operating conditions, e.g. varying cathode emissivity and accelerating potentials, to ensure that the design requirements were met over the working range of the gun. The scoring system was required to combine assessment of the operation at all the different conditions.

For materials processing applications there are a number beam characteristics of particular relevance. For example, in electron beam welding, where the beam penetrates into material thicknesses that can be up to several hundred millimetres, the ability of the beam to form a vapour filled deep cavity (referred to as a keyhole) is dependent upon its intensity. In addition, the depth of focus of the beam, which is related to the beam angle, typically will be of greater importance for thicker section welding. Brightness is an inherent quality of an electron beam, and is defined as the ratio of the focused spot intensity to the beam solid angle. High brightness indicates that an intense and near parallel beam could be formed by the right electron optical elements. It also indicates that a very intense spot could be formed for a high angle beam.

The use of beam brightness alone as a score of the gun design may lead to impractical designs where the beam produced was of such high diameter that the lens and deflection coils became too large. Consequently, the scoring system needed to combine a number of factors, such as brightness and beam width in the lens. These factors were weighted according to their relative importance. Some of the additional factors required the electron beam to be analysed after the focusing lens – for example to look at the focused beam spot size at the work piece.

Within this work 2-D models of the electron gun were used and trajectory plotting was carried out in two dimensions. This is accurate for the vast majority of electron guns used for materials processing, which are axi-symmetric. The trajectories produced by the analysis software were described by a velocity vector and radial position when at a specified axial position beyond the anode. Each trajectory carries a portion of the beam current, and this information is also extracted. This can be used in current weighted average calculations of the beam radius and angle. The solution time for a single model was typically less than 1 minute.

Although the beam could have been examined after the lens by modelling the complete gun column, this would have been computationally expensive, leading to extended solution times. To speed up the analysis, algorithms have been developed that allowed the beam trajectories to be projected forward and through the focusing lens. For most materials processing electron beam systems the lens aberration could be neglected and it was therefore not necessary to model the magnetic lens field and plots the trajectories of the beam through it. In addition, errors accumulate with trajectory plotting such that plotting overlong path lengths would be inaccurate. Instead, a mathematical model of the lens was used and the trajectories calculated from the gun, through the lens to their focal position at the work piece. Intensity plots across the focused beam spot were then calculated which allowed beam intensity metrics to be derived such as the full width at half maximum (FWHM), the full width at half power (FWHP) and the current weighted average (CWAD) diameter, see for example figure 2. A useful metric of beam quality is given by the brightness, defined as

$$B = \frac{J}{\Omega}$$

where $J$ is the beam spot intensity and $\Omega$ is the beam solid angle. This quality is invariant, in practical terms, for material processing type electron guns, as the electron lens aberration is comparatively insignificant.

Consequently, a number of beam metrics were derived from the trajectory files, which could then be used subsequently as a measure of the gun design fitness in order to enable selection of better designs within a population as part of a design evolutionary algorithm.

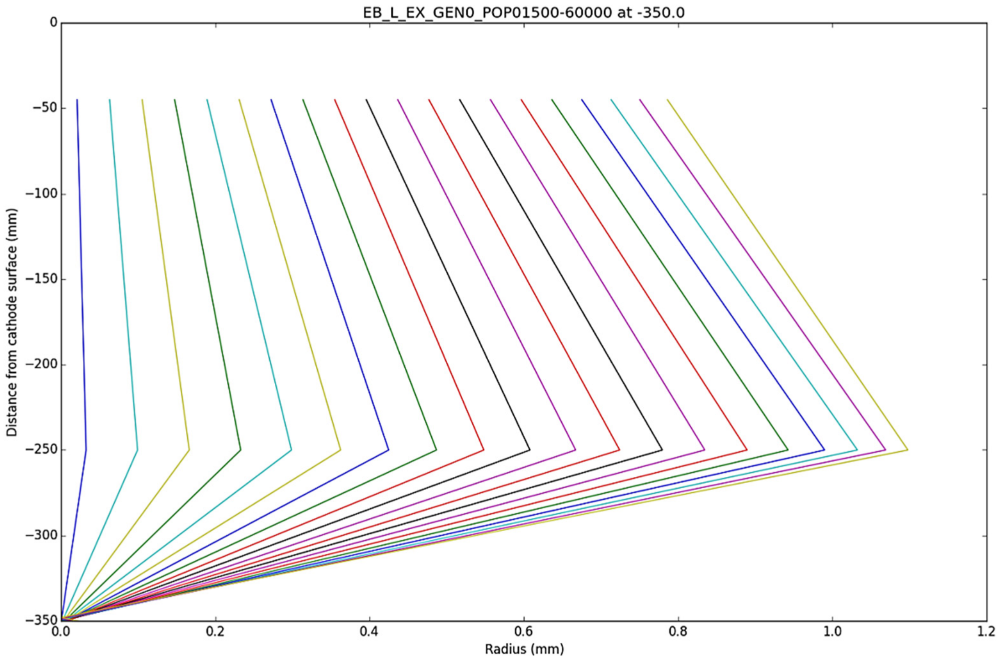


Figure 2(a): Example of a ray diagram after projection of trajectories from the gun model through a mathematical lens to their focus at the work piece.

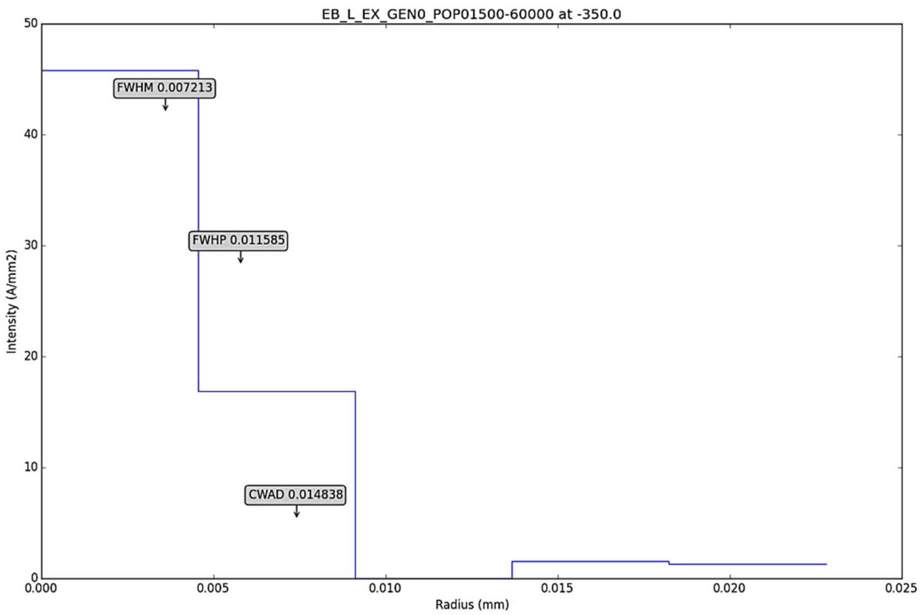


Figure 2(b): Example of a beam intensity plot after projection of trajectories from the gun model through a mathematical lens to their focus at the work piece.

## 3.2 Genetic Coding of the Design

To apply evolutionary design techniques it is necessary to include the design into a genome. The genome is a collection of genes that describe the design. For an electron gun, designed in 2-D, a geometry was specified describing the anode, high-voltage electrodes and the cathode. Each line within the geometry had a starting and stopping position and a degree of curvature. These parameters provided a means of describing the geometry as a series of genes. An example of the geometric description is given in Table 1, which could be directly translated into a model by the simulation software. Each row in Table 1 described the next corner of an electrode, cathode or anode shape. The corner coordinates were given as real values, XP and YP, and the discretisation of the line, which gave higher mesh resolution for curved lines for example, was given by the parameter N. Other parameters that were not varied by the evolutionary algorithm were also defined e.g. F, which was the boundary condition for the model at that face.

Table 1: Example of geometric description of part of an electrode in an electron gun.

| | |
|---|---|
| 1 | CARTESIAN YP=-38.7 CURVATURE=0 N=17 XP=7.95 |
| 2 | CARTESIAN XP=100 N=93 YP=-38.7 CURVATURE=0.0 |
| 3 | CARTESIAN YP=-50 N=12 F=NO XP=100.0 CURVATURE=0.0 |
| 4 | CARTESIAN XP=2.75 N=98 YP=-50.0 CURVATURE=0.0 |
| 5 | FINISH N=12 F=V |
| 6 | QUITDRAW |
| 7 | GROUP NAME=ANODE |

Each of the shapes within the gun design were defined in a similar manner to Table 1, and together these formed the complete genotype.

The special adaptions that have been made to evolutionary methods to allow them to be implemented for electron gun designs were:

• A change genome was constructed that contained only those parts of the design that can be changed and to which evolutionary processes can be applied

• A generic genome was constructed that described the rest of the design, and which when added to the change genome described a complete gun design

• The allowable range of any position or line curvature in the change genome was encoded within it to (a) constrain solutions within practical limits and (b) scale any mutation to that range

• Gene splitting was only carried out between genes so that mutation could be controlled discretely.

There were a number of constraints on the geometry that could be accommodated. The approach taken within this work to recognise these constraints was to take, in preparation for the design optimisation algorithm, two geometries which described the full range of design freedom. These two geometries were examined by an algorithm to produce a 'change genome' containing just those parts of the model that were different in the two geometries. Those parts of the model that were completely constrained, i.e. the same in the two geometries were not genetically encoded. These were described within a template similar to Table 1 and recorded in a single generic genome to be used for all the designs.

The change genome was used whenever a gene was mutated. The mutation was constrained within the limits for that position or line curvature and the scale of mutation was normalized to the range for that position or curvature. Combining the new genome with the generic genome gave a description of the complete gun design.

The following steps were carried out to implement the design evolution process:

i. An initial population of electron gun design variants was generated by producing genomes made from a randomised set of change genomes combined with the generic genome.
ii. Each of the electron gun designs was analysed using a finite element space-charge solver and electron trajectory vectors for beamlets from the cathode determined as they left the gun
iii. For each of the electron gun designs, the electron trajectory data was used to produce beam quality metrics (brightness, intensity, angle and beam width) through calculation of the trajectory path mathematically traced through an electron lens to the work piece
iv. The beam quality metrics were then used to derive a fitness score for the design. This score depended upon the requirements for the gun e.g. maximise the beam brightness and minimise the beam angle
v. Those designs with the best fitness score were selected to produce a 'parent group'
vi. The next generation of designs was produced from this group by choosing two designs randomly and splicing a random section of one change genome into the other. The genome was only split between genes to avoid mutations caused by splits occurring within a gene. Random mutation of any one of the change genes was also implemented in this stage. The new change genomes were combined with the generic genome to produce the new generation of gun designs.
vii. The parent group and the new generation formed a new population, which was then put through the same process until a preselected satisfactory fitness score was achieved.

The process therefore was designed to have a number of features anticipated to be of benefit to the particular challenge. A good design genome was promoted to the population forming the next generation until its fitness score ranking was not high enough. This ensured that each generation's parent group was at least as good as the last, and is a process termed elitist selection. This feature has been investigated, as there was concern that elitism may allow local maxima of the optimisation function to dominate.

By splicing the genes from two parents, a section of the design was copied to the child with the rest remaining the same as one of the parents. In genetic algorithm terminology this was a two point crossover function. The splicing respected the database structure of the genome to avoid mutation of the design due to corrupting the database. This was achieved by using ensuring that the data format as represented in Table 1 was maintained. However, some mutation was introduced to a controlled level to ensure that the design space was adequately explored.

In summary, the evolutionary process was implemented with special adaptions to make it suitable for electron gun design using modelling software and working within practical physical constraints.

### 3.3 Evolution Parameters

The main parameters for the evolution process were the parent group size, the offspring group size, the probability of gene mutation and the scale of gene mutation. These parameters generally determine the efficiency of the optimisation process, i.e the time taken for optimisation and the exploration of the problem space. Although many publications quote the evolution parameters used, there is little justification for the choices taken (Karafotias et al. 2014). Within this work, an analogous design problem to electron guns has been used to examine the effect of different parameters on the evolutionary optimisation process.

The analogous problem chosen is one of shape fitting. The problem is to find the coordinates of the corners of a target shape. The fitness function is the inverse of the sum of the distances of mismatch between the potential solution corners and the target shape corners.

This problem is useful for examining the effect of evolutionary parameters because it is dealing with coordinate values, as in the electron gun optimisation. It is also scalable in terms of complexity – so the effect of increasing the number of corners in the target shape can be examined.

This problem differs from electron gun design optimisation in that the fitness function has a single solution and varies smoothly, which would not be expected for an electron gun being scored on the electron beam optical qualities. However, tests carried out with this problem, described in section 4, give an insight into identifying the best evolutionary parameters for optimisation.

## 4 DESIGN TRIALS

### 4.1 Shape Evolution

The objective of this trial was to determine the most efficient settings of the evolutionary parameters for solving a shape fitting optimisation. This has been carried out for 3, 5, 8 and 10 cornered shapes. For 13 cornered shapes, the individual optimisations were taking too long to allow practical trials over a wide range of evolutionary parameters. Efficiency was measured by recording the total number of calls to the scoring function for each optimisation – this must be done for the initial parent group and each generation of offspring. In the analogous electron gun design optimisation, a call to the scoring function would require a model solution and trajectory analysis, taking up to 1 minute. In this case, a call to the scoring function took under 1msec, allowing a large number of trials to be carried out.

For the 3 to 10 cornered shapes, the number of offspring has been varied from 2 to 100, the parent group from 2 to 30, the mutation scale from 0.05 to 1 (5% to 100%) and the mutation rate from 0.01 to 0.1 (1% to 10%). In total, the different combination of parameters led to 42,000 optimisations being executed for each shape. Each optimisation required from 338 (fastest 3 cornered) to over 200,000 calls (slowest 10 cornered) to the scoring function.

The results were analysed by plotting the number of calls as a function of the number of offspring and number in the parent group, see figure 3(a) and the mutation rate and mutation scale, see figure 3(b), both for 10 cornered shape evolution. Also, sampling was carried out of the most efficient 1% of optimisations for each shape and the modal evolutionary parameter settings were extracted – see figures 4(a) and (b).

The results show that a small parent group of 2 or 4 is most efficient over all the range of shapes. It is also clear that as the number of corners increases the optimum values for mutation rate decreases. For 3 and 5 cornered shapes the optimum mutation scale is 0.15 dropping to 0.1 for 8 and 10 cornered shapes.

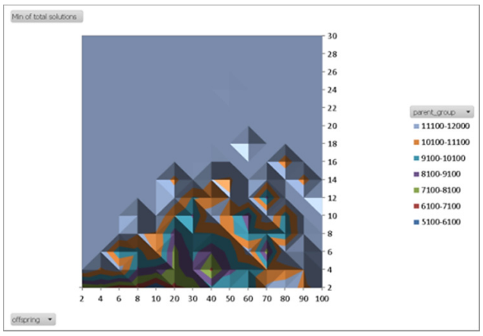


Figure 3(a): The number of score function calls as a function of the parent group and offspring group sizes.

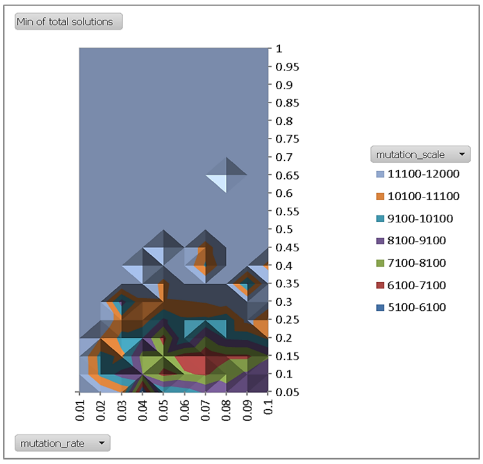


Figure 3(b): The number of score function calls as a function of the mutation scale and mutation rate.

For 3 cornered shapes the optimum mutation rate is 0.1, decreasing to 0.06 for 8 cornered shapes and 0.05 for 10 cornered shapes. This is shown in figures 4(a) and (b).

In summary, this trial has shown that as problem complexity increases the optimum mutation rate and scale for rapid optimisation will be lower. It

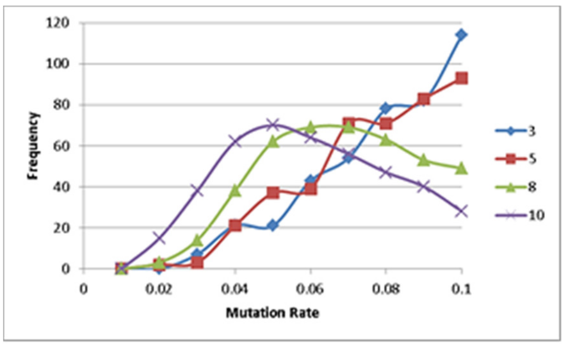


Figure 4(a): Histogram of the top 1% optimisations showing decreasing mutation rate with increasing problem complexity.

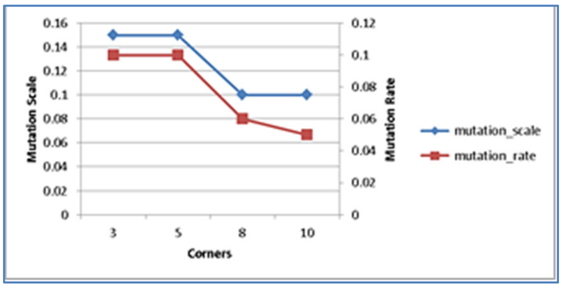


Figure 4(b): Modal values of mutation scale and mutation rate of the top 1% efficient optimisations.

indicates that values of mutation rate and scale should be used of less than 0.05 and 0.1 respectively. Regardless of problem complexity, parent groups of 2 or 4 are the most efficient, as are offspring numbers of 10 or less.

These results were then used to determine the evolutionary parameters for an electron gun design problem.

## 4.2 Anode Shape Evolution

The electron gun evolutionary design process was applied to a novel radio frequency (RF) excited plasma cathode gun design (del Pozo et al., 2014; Ribton and Sanderson, 2012). This type of gun design is a diode having a high-voltage electrode and cathode at the same potential. The cathode is a plasma, but for simulation purposes the cathode surface has been modelled as a lanthanum hexaboride thermionic emitter over a range of temperatures and therefore emissivities, producing electrons with no thermal energy.

The gun design was required to produce an intense electron beam at focus, therefore of high brightness, and produce a reasonably low angle beam so that it could pass through an existing gun column with a constriction at the electron lens. However, too low an angle beam would give poor electron optic magnification so an optimum beam diameter of 4mm at the lens position (150mm from the cathode) was chosen. These requirements are summarised in Table 2.

Table 2: RF plasma gun beam requirements.

| Metric | Requirement |
|---|---|
| Diameter at 150mm from cathode | Ideally 4mm |
| Brightness | > 5000 Amm$^{-2}$sr$^{-1}$ |

Weighting factors were used for each of the metrics as the design fitness test needed to look at more than one requirement in order to allow ranking of the design variants in the population. The scoring function is described in the following pseudo-code:

```
   Over the cathode temperature range
1450 – 1600K and for 30kV and 60kV
accelerating potentials:
   score = add Log(brightness)*beam
current
   If beam current <20mA
   If 1/(beam diameter 150mm from
cathode – 4) >10
   Add 10
   Else
   add abs(1/(beam diameter 150mm from
cathode – 4))
```

The evolution parameters used in this trial are presented in Table 3.

Table 3: Evolutionary algorithm parameters.

| Parameter | Value |
|---|---|
| Parent group size | 4 |
| Offspring group size | 6 |
| Mutation scale | 0.1 |
| Mutation probability | 0.07 |

Table 4(a): 1st Generation population ranked scores.

| Model | Score |
|---|---|
| Gen_0_Pop_1 | 2.37 |
| Gen_1_Pop_6 | 2.10 |
| Gen_1_Pop_4 | 2.10 |
| Gen_0_Pop_3 | 2.09 |
| Gen_1_Pop_5 | 2.09 |
| Gen_0_Pop_0 | 2.03 |
| Gen_1_Pop_7 | 2.02 |
| Gen_1_Pop_8 | 2.02 |
| Gen_0_Pop_2 | 2.01 |
| Gen_1_Pop_9 | 2.01 |

Table 4(b): 10th Generation population ranked scores.

| Model | Score |
|---|---|
| Gen_10_Pop_4 | 11.59 |
| Gen_6_Pop_4 | 3.57 |
| Gen_8_Pop_6 | 3.57 |
| Gen_9_Pop_5 | 3.57 |
| Gen_10_Pop_6 | 3.57 |
| Gen_10_Pop_7 | 3.57 |
| Gen_9_Pop_7 | 3.23 |
| Gen_10_Pop_5 | 3.03 |
| Gen_10_Pop_8 | 2.89 |
| Gen_10_Pop_9 | 2.65 |

The designs were labelled with a generation number and a population number, e.g. Gen_1_Pop_5 was the 5th offspring produced in the first generation. A log was kept of the scoring – this is shown for the 1st generation in Table 4 (a) and for the 10th generation in Table 4 (b).

The progress of the automatic design algorithm was monitored through the plotting the best fitness score of each generation. This is presented in Fig 5.

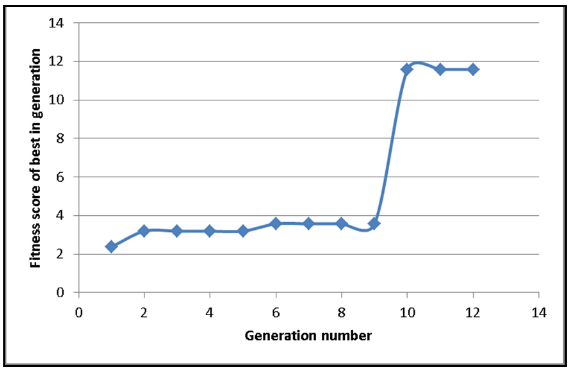


Figure 5: The best fitness score in successive generations.

The use of an evolutionary algorithm for the electrode optimisation allowed designs meeting the requirements to be found within 2 to 3 hours of computing time without human expert intervention. This compares well with normal trial and error design requiring frequent expert intervention over a period of 10 to 15 hours. The ability to template constrained parts of the design was useful in ensuring that the algorithm only explored mechanically viable designs making it more efficient. Further comparison with other optimisation methods will be carried out in the future as details of solution times for electron gun optimisation methods are not published at this time

# 5 CONCLUDING REMARKS

Electron beam gun design is at best a trial and error process. An evolutionary design algorithm has been implemented which enables the automatic design of an electron beam gun to produce electron beam with characteristics to meet specified requirements. This algorithm has been trialled on a novel RF excited plasma cathode gun design and shows promising results.

Analysing electron guns and deriving electron beam characteristics is necessary within any automatic design process in order to assess the suitability of the design to meet requirements. However, this is a process that uses substantial computing resource. Until recently, the solution times required meant that solving the large number of designs that necessarily make up a population was impractical on normal desktop computers and was expensive if implemented on multicore supercomputers. Current analysis software for analysing electron beam guns in 2-D are relatively fast. For example, a 10,000 element model of an electron gun will converge to a solution, taking into account the space charge of the electron beam, in a time of less than 1 minute running on a desktop PC. These recent advances in software implementation and computing hardware have made the implementation of automatic design algorithms possible.

There are two key steps in implementing and evolutionary algorithm for design: the design features to be evolved must be encoded in a genome, and the suitability of the design must be able to be quantified in a fitness score. As such the implementation of evolutionary algorithms for design could be applied to a very wide range of design challenges.

Within this work an evolutionary design algorithm for electron guns was developed and tested. As a single optimisation can take several hours, the evolutionary parameters have been estimated from an analogous problem of shape fitting, where many thousands of solutions could be analysed. In future work, more exploration of tuning of evolutionary parameters will be carried out, and automatic adjustment of the parameters at different stages of the optimisation will be explored.

Monitoring of the score function for the best of each generation shows incremental improvements and on one occasion a significant jump going from one generation to the next. In this work, the optimisation process has been run several times and this usually occurs, corresponding to a mutation or gene spliced combination of features that gives a near optimum diameter of beam in the lens and a high brightness.

There are, however, a wide range of meta-heuristic methods for design optimisation which could be applied. At this time one of the most popular and most promising methods is particle swarm optimisation. The work carried out on including the design and the software implementation of an automatic design method will in the near future be applied using alternative optimisation techniques. It is also intended to monitor the design optimisation convergence and adjust the applied technique to converge at the highest rate. This offers the tantalising possibility of being able to optimise the optimisation method, for example, the evolutionary process could itself evolve to become ever more efficient.

From the work reported the following conclusions can be drawn

- A technique has been developed to allow electron gun designs to be automatically optimised
- Assessment of a gun design against required electron beam characteristics has been quantified by deriving key beam qualities from field analysis and trajectory plotting
- An evolutionary design optimisation method has been tested
- The design method has been applied to a novel plasma cathode electron gun.

# ACKNOWLEDGEMENTS

This work has been supported by The National Structural Integrity Research Foundation, TWI Ltd and Brunel University London.

# REFERENCES

Biddlecombe, C. & Simkin, J., 1983. Enhancements to the PE2D package. Magnetics, IEEE Transactions on, 19(6), pp.2635–2638.

Clerc, M., 1999. The swarm and the queen: towards a deterministic and adaptive particle swarm optimization. In Evolutionary Computation, 1999. CEC 99. Proceedings of the 1999 Congress on.

Denies, J., Ahmed, H.B. & Dehez, B., 2013. Optimal design of electromagnetic devices: development of an efficient optimization tool based on smart mutation operations implemented in a genetic algorithm. Mathematics and Computers in Simulation.

Dorigo, M., Caro, G.D. & Gambardella, L.M., 1999. Ant algorithms for discrete optimization. Artificial life, 5(2), pp.137–172.

Franz, R., 2006. Representations for genetic and evolutionary algorithms. Springer-Verlag Berlin Heidelberg.

Hawe, G. & Sykulski, J., 2007. Considerations of accuracy and uncertainty with kriging surrogate models in single-objective electromagnetic design optimisation. Science, Measurement \& Technology, IET, 1(1), pp.37–47.

Hawe, G.I. & Sykulski, J.K., 2008. A Scalarizing One-Stage Algorithm for Efficient Multi-Objective Optimization. IEEE Transactions on Magnetics, VOL. 44, NO. 6.

Herrmannsfeldt, W., 1988. EGUN: An electron optics and gun design program.

ISO, 2008. Welding - Acceptance inspection of electron beam welding machines - Part 1: Principles and acceptance conditions.

Jiang, W. et al., 2015. Genetic Algorithm-Based Shape Optimization of Modulating Anode for Magnetron

Injection Gun With Low Velocity Spread. IEEE Transactions On Electron Devices, VOL. 62, NO. 8.
Kirkpatrick, S., Jr., D.G. & Vecchi, M.P., 1983. Optimization by simulated annealing. Science, 220(4598), pp.671–680.
Karafotias, G., Hoogendoorn, M. & Eiben, A., 2014. Parameter control in evolutionary algorithms: Trends and challenges. IEEE Transactions on Evolutionary Computation, to appear. Lebensztajn, L. et al., 2004. Kriging: a useful tool for electromagnetic device optimization. Magnetics, IEEE Transactions on, 40(2), pp.1196–1199.
Lewis, B.M. et al., 2004. Design of an electron gun using computer optimization. Plasma Science, IEEE Transactions on, 32(3), pp.1242–1250.
Pierce, J.R., 1954. Theory and design of electron beams.
Del Pozo, S., Ribton, C. & Smith, D.R., 2014. Characterisation of an RF excited argon plasma cathode electron beam gun. In Vacuum Electron Sources Conference (IVESC), 2014 Tenth International. pp. 1–2.
Ribton, C. et al 2015. Plasma source apparatus and method for generating charged particle beams. US Patent 9076626B2.
Sykulski, J.K., 2008. New trends in optimization in electromagnetics. In Computation in Electromagnetics, 2008. CEM 2008. 2008 IET 7th International Conference on. pp. 44–49.