Genetic Algorithm Optimization of Transcutaneous Energy Transmission Systems For Implantable Ventricular Assist Devices

Kelly Byron *Member, IEEE*, Vlad Bluvshtein *Member, IEEE*, and Lori Lucke

Abstract— **Transcutaneous energy transmission systems (TETS) wirelessly transmit power through the skin. TETS is particularly desirable for ventricular assist devices (VAD), which currently require cables through the skin to power the implanted pump. Optimizing the inductive link of the TET system is a multi-parameter problem. Most current techniques to optimize the design simplify the problem by combining parameters leading to sub-optimal solutions. In this paper we present an optimization method using a genetic algorithm to handle a larger set of parameters, which leads to a more optimal design. Using this approach, we were able to increase efficiency while also reducing power variability in a prototype, compared to a traditional manual design method.**

I. INTRODUCTION

Transcutaneous energy transfer systems (TETS) are a method to wirelessly deliver power through the skin using a time-varying electromagnetic field. TETS can be used to power a ventricular assist device (VAD), eliminating the need for wires going through the skin and thereby greatly reducing the patient's risk of infection.

A two coil TETS system for a VAD application is shown in Fig. 1. The primary coil is worn outside the body, while the secondary coil is implanted. The amount of current that is induced in the secondary coil, and therefore the amount of power that is transferred, is dependent on the coupling coefficient of the coils. The coupling coefficient is determined by the coil size and the distance between coils. In a real life VAD application, this means that the coupling between the coils will fluctuate, making the efficiency and delivered power susceptible to significant variations.
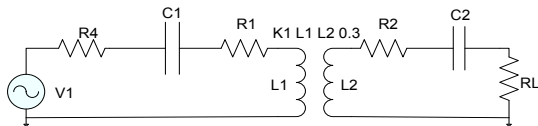

Figure 1. Inductive Link Circuit Model

Optimizing the inductive link requires choosing parameters that transfers the minimum amount of output power required while achieving the maximum efficiency in the design. In addition, the TETs system must minimize the variability of efficiency and delivered power to tolerate changes in the coupling coefficient.

K. Byron is with Stanford University, Stanford, CA 94305 USA (e-mail: kbyron@ stanford.edu).

V. Bluvshtein is with Minnetronix, Inc., Saint Paul, MN 55108 USA (e-mail: vbluvshtein@minnetronix.com).

L. Lucke is with Minnetronix, Inc., Saint Paul, MN 55108 USA (e-mail: lelucke@minnetronix.com).

There are several techniques that exist to optimize the design [3,4,5,6]. These methods are fairly constrained in the number of parameters that can be made variables in the optimization. They have a higher risk of converging on a local maximum, instead of finding the global optimal solution. One way to open up the search space in order to find a better design is to use a genetic algorithm. This method was originally introduced in [1] using a low power example. In this paper we build on this approach. We compare the genetic algorithm approach to a solution found using manual optimization. We construct a prototype to verify the results of the genetic algorithm approach. We also expand the approach to the much higher power levels common to VADs.

II. OPTIMIZATION COMPARISON

A. Manual Approach

To evaluate the results of the genetic algorithm approach, we compare the solution to a manual method used to optimize the inductive link. The manual method uses critical coupling [2] as shown in Fig. 2. The critical coupling solution supports a small coupling coefficient, which is important for a wearable design. The disadvantage of using a critically coupled design is that the efficiency can never be higher than 50%.
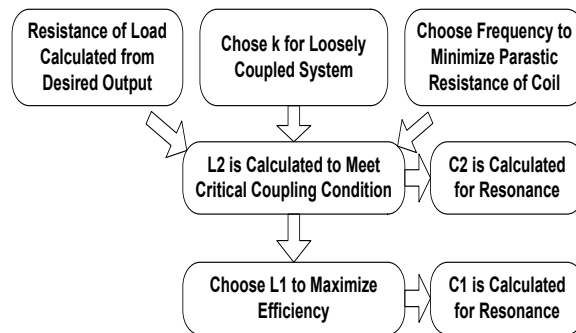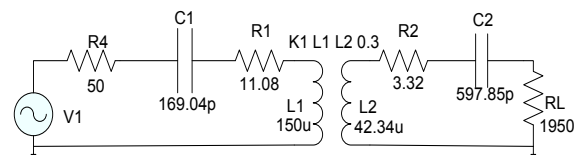

Figure 2. Critical Coupling Design Method

Figure 3. Critical Coupling Circuit Model

To allow for a simple optimization approach, the coupling coefficient was fixed to k = 0.3, which allows for a realistic

separation between the coils. In addition, the frequency was fixed at 1MHz to limit the parasitic resistance of the coils. The link model was then manually optimized using the critical coupling approach and by using a SPICE simulation as shown in Fig. 3.

The results for the calculations at k = 0.3 are shown in Table I and compared to the results from a SPICE simulation using the same component values. When comparing delivered power and efficiency over varying k values, the results shows low power variability that was the objective of using the critical coupling method.

TABLE I

	Calculation	SPICE Simulation
Power (mW)	25.458	23.589
Efficiency	18.40%	15.13%

B. Genetic Algorithm

Using a genetic algorithm, it is possible to explore a larger solution space than with the manual method. One important way that the solution space is expanded is by including the efficiency and power variability over the range of the coupling coefficient values as objectives of the solution. The genetic algorithm is given a function to optimize with three objectives. Maximize the efficiency while minimizing the power variability and efficiency variability to changes in the coupling coefficient. These objectives, in Eq. 1, were given different weights so that the algorithm could determine their importance and optimize the function accordingly.

$$y = P\_var^{0.5} * (1/E_{mean})^{0.4} * E\_var^{0.1} \quad \text{eq. (1)}$$

The power variability was given the highest weight, since in real life VAD applications the distance between the coils, and therefore the coupling coefficient, will vary from patient to patient and as the patient moves around. Efficiency was also weighted as important, because inefficient designs lead to power being dissipated through the coils as heat, which becomes especially dangerous in the implanted coil where excess heat can cause serious tissue damage. In addition to the optimization function, the algorithm was also given the constraint that the solution should deliver at least 8mW of power at k = 0.3. The delivered power was limited to show the viability of this approach and allow a simple prototype to be built. For a VAD application, 20W of power would be more typical.

The genetic algorithm finds a solution that is the best fit for all three objectives at the same time. This is a big improvement over the manual method outlined above where fixed parameters limit the solution. This is also an improvement over other methods, such as adding series compensation capacitors [5,6], which improve overall efficiency but still fix k as a parameter.

Fig. 4 gives an outline of the method used with the genetic algorithm. The algorithm allows for upper and lower bounds on the values it can choose for variables, so the inductance values were constrained to be within the limits of what could be made in a physically realizable design. Setting bounds also allowed us to make frequency a variable. In this way the genetic algorithm allowed us to vary more parameters then in the critical coupling method, where frequency was set to a fixed value at the beginning of the calculations.
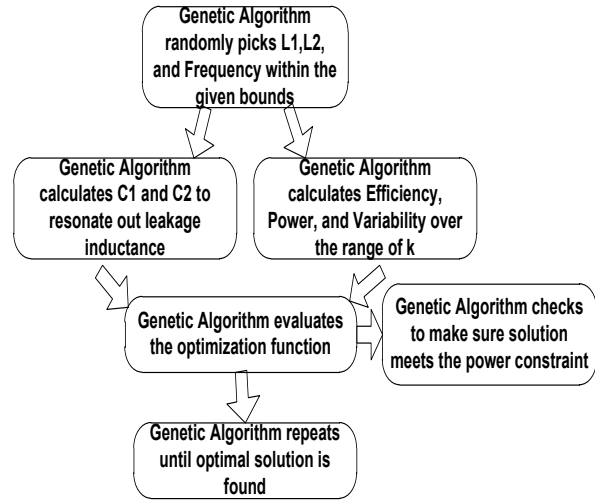

Figure 4. Genetic Algorithm Design Method

Another difference from the manual critical coupling method is that the genetic algorithm picks the inductance values independently of one another, as well as independent of frequency. This also opens up the search space because the order the parameter values are calculated is no longer important. The order parameter values are fixed is important not only in designs following the critical coupling method [2,3], but also in most other commonly used manual approaches, such as stagger tuning [7], adding compensation capacitance [5,6], or using a three or four coil design to improve the efficiency and variability [4]. In these approaches constraining the order parameter values are chosen simplifies the calculations at the cost of finding a less optimal solution.

Similar to the critical coupling method, the capacitance values were computed by the algorithm to resonate out the leakage inductance. Originally the capacitance values were also variables in the algorithm, but the performance of the algorithm improved greatly when they were calculated for resonance.

The solution is shown in Fig. 5. Table II compares the values calculated by the genetic algorithm to SPICE simulation results for the same component values. When comparing delivered power and efficiency over varying k values, the results show low power variability and low efficiency variability which is an improvement compared to the critical coupling method.
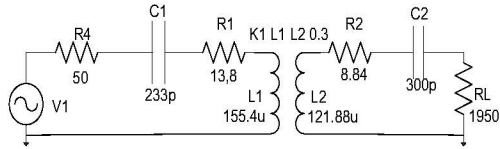
Figure 5. Genetic Algorithm Circuit Model

C. Genetic Algorithm Prototype

A prototype was made to verify the results achieved through the genetic algorithm. The value of the load was chosen so that a simple prototype could be made to measure the actual performance of the design. This load is relatively small, so using a parallel resonance on the secondary side would lead to a higher efficiency since the design is limited to practical values for the components. However, VADs drive high loads that have low impedance, so it is desirable to use a series resonant capacitor for these applications. Therefore, we used a series capacitor in the prototype, even though it limits the efficiency, in order to make the circuit as similar as possible to what would be used for an actual VAD design.

The measured results in Table II show a lower efficiency than expected since there was a linear voltage regulator on the output with poor efficiency. This prototype shows that the genetic algorithm gave valid results that can be achieved in an actual inductive link but that efficiency is affected by the regulator as well as within the link.

TABLE II

	Calculation	SPICE Simulation	Measured Results
Power	8.30 mW	8.63 mW	8.39 mW
Efficiency	34.31%	33.04%	20.50%

I. COMPARISON OF RESULTS

Table III shows a summary of the results for the manual approach and the genetic algorithm approach. Using the genetic algorithm, the solution was improved substantially, with a doubling of efficiency and significantly reduced power variability. The efficiency variability did increase by a small amount in the genetic algorithm results, but this reflects the low priority weighting given to efficiency variability in the genetic algorithm. The tradeoff in efficiency variability was well worth improved results in the other areas and may not have been obvious with a manual solution.

TABLE III

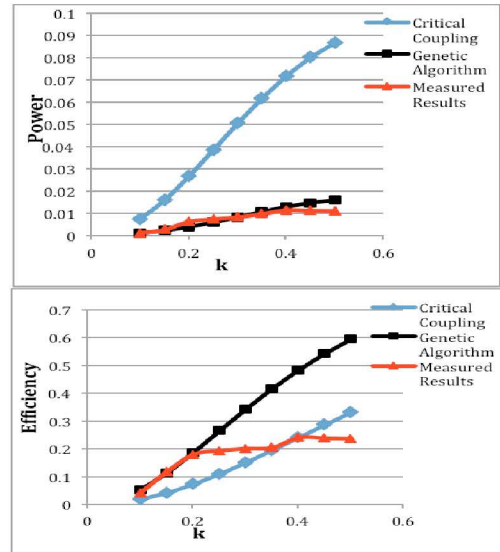|	Critical Coupling	GA Method
Power at k =0.3	5.05 mW	8.3 mW
Average Power	4.89 mW	8.4 mW
Power Variability	8.10E-04	3.00E-05
Efficiency at k=0.3	15.21%	34.31%
Average Efficiency	16.19%	33.33%
Efficiency Variability	1.21%	3.66%

Figure 6. Comparison of Results with Varying k

The improved power and efficiency results for varying k are shown in Fig. 6. This demonstrates the utility of the genetic approach to providing a more optimal link model. In the future, different objectives, such as lower efficiency variability, could be further improved by changing the weights on the optimization function given to the genetic algorithm.

II. EXTENDING TO HIGHER OUTPUT POWER

The first example shown above demonstrates the utility of the genetic algorithm approach. The small amount of power provided by this solution is not sufficient for a VAD application although it did allow for building a prototype to demonstrate that the theory matches well with practice. Powering a VAD requires significantly more power than the previous example.

Using the genetic algorithm design a solution sufficient to power a VAD requires changing the load impedance to that of the motor controller and changing the minimum power requirement to 20W. Transferring 20W of power requires much smaller parasitic loss in the coils, which would not be realizable with the simple copper wire used in our prototype coils but can be achieved through the use of Litz wire. Litz wire is commonly used for applications where low parasitic loss is required. To make a practical VAD device the inductances would also need to be constrained to less than 20uH in order for the coils to be small enough to be implanted.

Changing the parameters to realistic values for an actual VAD, a closed form solution and the genetic algorithm were applied to generate solutions. In a VAD, the input and output voltages have to be compatible with the motor requirements as well as the battery system. In addition the frequency must be limited to prevent absorption by the skin tissue. The following parameters were used: k = 0.1-0.27, V_{in} = 20V, V_{out} = 15.5V, R_L = 12 Ohm, P = 20W, f_o = 500kHz.

A closed form solution was generated with the assumption that the primary and secondary resonate at the same frequency. This allows the ability to rewrite the link equations in terms of Q and thus derive a simple closed form solution. For this example, the closed form solution used the maximum link efficiency method as shown in Fig. 7 [8].
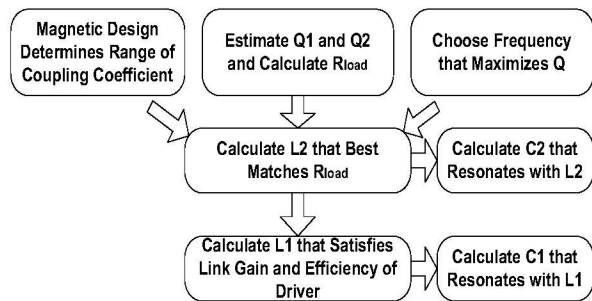

Figure 7. Maximum Link Efficiency Method

The genetic algorithm was setup with the following constraints:

Minimize

$$\beta(L1,L2,f1,f2):=E(L1,L2,f1,f2)^{k1}*Var[V_{out}(L1,L2,f1,f2)^{k2}]$$

Subject to: minimum required output voltage, coupling range, load variation, (L1, L2) range, and with (L1, C1) resonant at f1, and (L2, C2) resonant at f2.

A comparison of the solutions was setup with an LTSpice simulation using a Class D amplifier and shunt switching regulator. Results are shown in Figs. 8 and 9. Again it is clear that the genetic algorithm generates an improved solution over the closed form solution. While the efficiency versus coupling is identical, the power loss in the coils is improved with the genetic algorithm
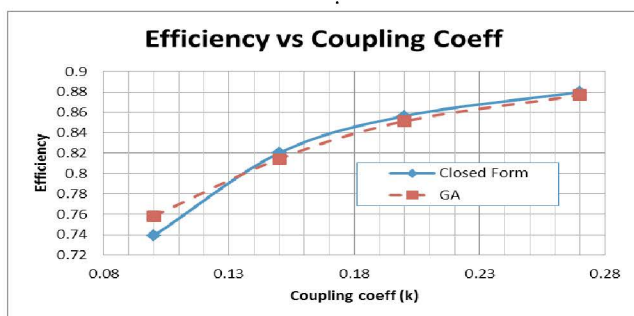

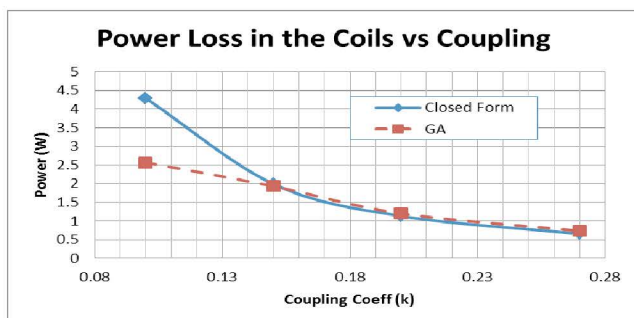Figure 8. DC-DC Efficiency vs. Coupling for Large Power Solution

Figure 9: Power Loss vs. Coupling for Large Power Solution

With the closed form solution the output voltage (power) increases monotonically as the coils separate and the load resistance increases. This excess power causes large circulating currents in the coils (I^2R losses) and losses in the secondary regulator.

With the genetic algorithm optimization, the link design is improved as it reduces the increase in output voltage as the coils separate. This results in lower I^2R losses in the coils and less stress on the secondary regulator. The tradeoff with this solution is that load impedance presented to the amplifier is non-resonant at the operating frequency. To handle this non-resonant behavior an amplifier must be used that can tolerate the non-resonance. Fortunately Class D amplifiers can handle this behavior. Therefore it is possible to take advantage of the improved performance provided by the genetic algorithm solution.

III. CONCLUSION

Optimizing a TET system using a genetic algorithm allows us to handle a larger set of parameters, which results in a more optimal design than traditional manual design approaches. By using the genetic algorithm the efficiency was doubled and power variability was significantly reduced. This was demonstrated for a low power output solution and a prototype was built to verify the solution.

In addition, a solution was generated for a VAD design that would transfer 20W of power with smaller inductances and parasitic resistances. This demonstrates that this approach can improve the link design for the large output power transferred in a typically VAD design.

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