Adaptive Impedance Tuning Network using Genetic Algorithm: ITuneGA

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***Abstract*—Adaptive impedance tuning algorithms are used to preserve the link quality of mobile phones under fluctuating user conditions. It is highly desirable to correct the complex impedance mismatch with high convergence rate. Presented here, is a novel technique for correcting impedance mismatch in adaptive impedance tuning network by exploiting the relationships among the genetic algorithm's coefficient values derived from the matching network parameters. Simulation results demonstrate that the proposed impedance tunable algorithm (ITuneGA) outperforms conventional GA and LMS, with its fast convergence speed and high accuracy. The robustness of ITuneGA has been verified by using Pi-networks with two and four tuning elements. ITuneGA corrects antenna impedance mismatches and reduces the reflected power, thereby significantly improving the quality of the signal.**

***Index Terms*—Tunable Impedance Network; Adaptive Algorithm; Genetic Algorithm; Impedance Network.**

I. Introduction

There is an increased demand for small size antennas for the next generation wireless devices. However, a small size antenna inherently has input impedance that varies rapidly with frequency and user environment, for instance the proximity of a mobile phone handset's antenna to the user's body [1-4]. The effects of hand and head to the performance of the antenna in mobile devices have been investigated in previous research works [5-8]. For example, how the phone is held by the hand can have an impact on antenna performance, as shown in Figure 1 **Error! Reference source not found.**[9]. The effects of antenna proximity have also been studied for talk and data modes based on the ways of a phone is held [10, 11]. These research works demonstrate that the presence of a nearby object degrades the radiation performance of the antenna in a mobile device severely. A large amount of received power is lost due to a change in the input impedance when the phone is closed with the user's hand, head, and body [1, 2, 12]. In some cases, the antenna becomes completely mismatched, which results in a loss of power in transceiver terminal [3]. This reduces the quality of the signal and it may even lead to serious reflections towards the power amplifiers.

To preserve the linearity under antenna mismatch conditions, an isolator is often applied between the power amplifier and the antenna to absorb the reflected power. However, this solution is not very attractive due to the maximum radiated power and the efficiency cannot be preserved using an isolator. Moreover, an isolator is a rather bulky and expensive component that cannot be integrated with other front-end functions [13, 14]. For this reason, an adaptive impedance tuning network is required to correct the antenna impedance mismatches and maximise the receiving power.

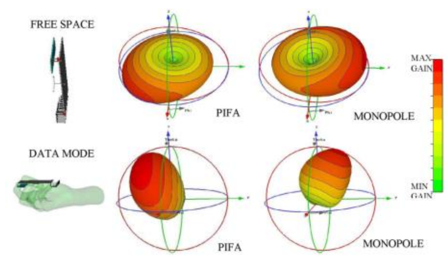


Figure 1: Effect of human hand (in data mode position) to the antenna gain patterns at 881.5MHz frequency [9]

II. Adaptive Algorithms

Linear correlation or stochastic methods based on adaptive algorithms are commonly used in the impedance matching networks [52, 67, 72, 73, 165, 170-174].

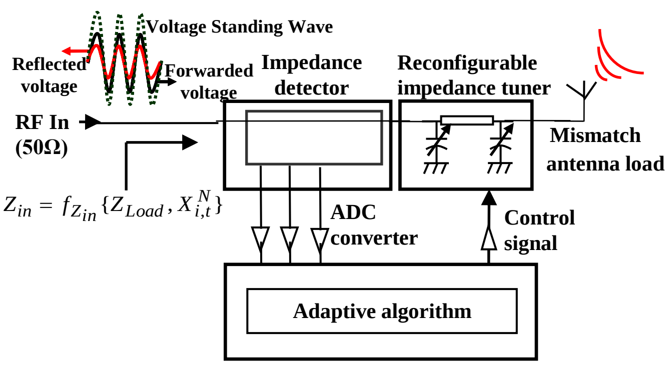
Linear correlation methods, such as the least mean square (LMS), have been reported for tuning the real [15] and imaginary [16] parts of the antenna impedance. LMS uses a gradient-based method of the steepest decent, in searching for the matched impedance tuning values. However, these methods are able to match either the real or imaginary part of the impedance but not both parts simultaneously due to the non-linear correlation of the tuner components. Furthermore, the linear methods require a large number of tuning steps for a small increment value. In a strong mismatch condition, larger increment values can be used, but it will be difficult in achieving the desired voltage standing wave ratio (VSWR). Recent work in reconfigurable impedance tuning network has involved a large number of tuning elements [17-20]. For instance, a tuning network based on a single stub with four tuning elements on the stub and six tuning elements on the transmission line has been used in [17], whereas eight tuning elements have been used in [18]. Some impedance tuning networks had even been designed with 11-12 tuning elements [19, 20]. To search potential complex impedance solutions from a large number of tuning elements, a random global search method is required.

Genetic algorithm (GA) has been proven to be a very powerful search method for many application areas. Genetic Algorithm works on an encoding of the parameter set and search globally in a population. GA has learning capability, and does not require function derivatives. They, thus fit to the natural of the tuning problem. This paper introduces an impedance tuner algorithm (ITuneGA) evolved from GA for adaptively correcting the impedance mismatches. The impedance tuner network parameters have been defined and formed as ITuneGA's coefficient values. The proposed algorithm demonstrates shorter convergence time and higher accuracy compared to the conventional GA in the domain of complex impedances.

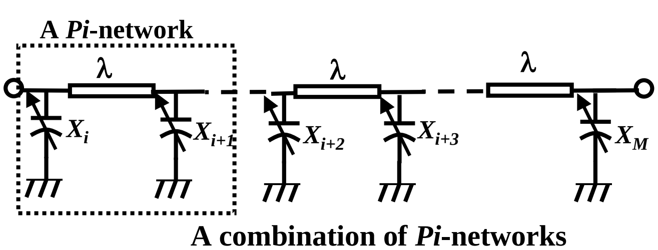
The remainder of this paper is divided into five sections. In Section II, we present the main impedance tuning network parameters. The methodology of GA is presented in Section III. The evolution of the proposed ITuneGA is presented in Section IV. The results and discussions are presented in Section V. Section VI concludes this work.

III. Adaptive Impedance Tuning Network

An adaptive impedance tuning network placed between the antenna and the RF front-end for correcting the impedance mismatch is shown in Figure 2(a). It consists of an impedance detector, an adaptive controller, and a reconfigurable RF impedance tuner. The impedance detector monitors the power, voltage and current relationships in the impedance network. The controller uses an adaptive algorithm to calculate the required tuning values in order to obtain a matched impedance state. The reconfigurable impedance tuner provides the required reactances to correct the impedance mismatch [21].



(a)



(b)

Figure 2: (a) Block diagrams of an adaptive impedance tuning network and their parameters (b) a *Pi* – network topology

The tunable impedance networks are evolved from the fixed impedance networks that have been used for precisely correcting the mismatch to the desired impedance. The impedance of the fixed network cannot be changed after implementation. To be reconfigured, RF switches need to be included in the impedance network. The impedance network designs transform the impedance of the RF switches to a range of impedance tuning region, which depends on their applications. For mobile applications, tunable impedance network designs require more stringent specifications, such as wide impedance coverage, a lesser number of RF switches, impedance network topology with small circuit size and losses, and less complexity in the biasing circuit.

The impedance tuner network is mostly based on a *Pi*-network or a combination of *Pi*-networks, as shown in Fig. 2(b). A *Pi*-network has good attenuation of harmonics compared to L-and T-networks. One of the disadvantages of a single *Pi* -network topology is that it cannot achieve full impedance coverage. Thus, a combination of *Pi*-networks is needed to achieve wide impedance coverage.

IV. Genetic Algorithms

The evolution of the proposed ITuneGA is governed by Genetic Algorithm (GA). GA uses a stochastic method in searching for matched impedance tuning values. GA mimics the metaphor of natural biological evolution. At each generation, new sets of approximations are created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process creates the population of individuals that is better suited to the environment than the population that was created from, just as in natural adaptation. The process of GA is presented in Figure 3.

Each chromosome would be assigned a fitness value through a customised fitness function. The fitness value drives the selection towards more fit individuals to be mated together during reproduction phase. New chromosomes will be produced in the next generation through GA's operators such as crossover and mutation. The new generation will be evaluated by the fitness function and the process continues through subsequent generations. The average performance of individuals in a population is expected to increase, as good individuals are preserved and bred with one another and the less fit individuals die out.

V. Adaptive Impedance Tuning Algorithm Using Tunable Genetic Algorithms

The input impedance (Z_{in}) is a function of the load (Z_{Load}) and an array of tuning element parameters (X_i). The Voltage Standing Wave Ratio (VSWR) is used as a measure of an impedance mismatch based on the reflection coefficient (Γ), as shown by Equations (1) and (2).

$$\Gamma = \frac{Z_{Load} - Z_0}{Z_{Load} + Z_0} \tag{1}$$

$$VSWR = \frac{1+|\Gamma|}{1-|\Gamma|} \geq 1 \tag{2}$$

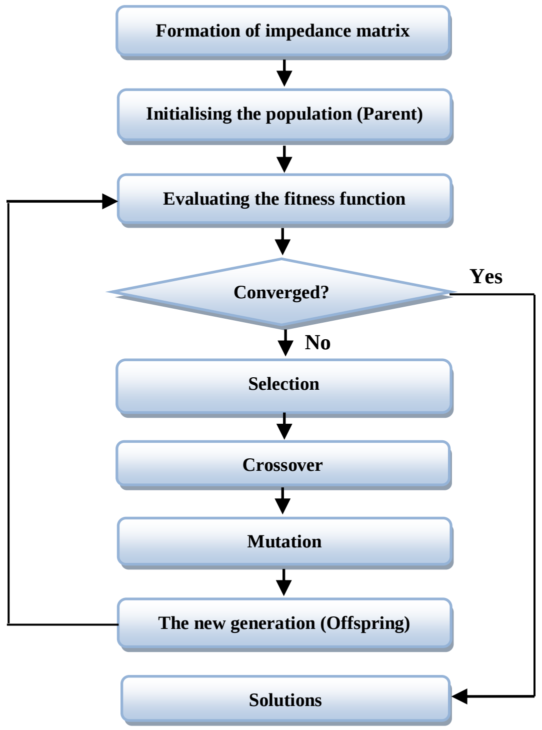


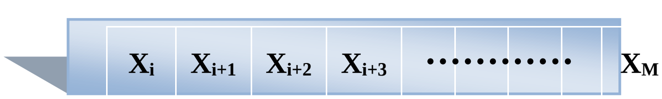
Figure 3: Process of GA

A. Population

Before proceeding with ITuneGA, formation of the impedance matrix based on tuning elements (X_i) is needed. X_i can be capacitive or inductive. Typically, implementation of tunable impedance network using capacitive devices is easier than the inductive devices. In this design, capacitive X_i is used in a *Pi*- network topology, as shown in Figure 2(b). The impedance matrix consists of chromosomes in N number, as shown in Figure 4(a). Higher number of N increases convergence speed but requires more computational resources. The chromosome is an array of tuning devices, as shown in Figure 4(b). The chromosome can be encoded in binary or real code. These chromosomes are arranged in such that the X_i values can be uniquely mapped onto the decision variable domain.

Number	Impedance matrix
1	Chromosome
2	Chromosome
…	Chromosome
…	Chromosome
…	Chromosome
N	Chromosome

(a)



(b)

Figure 4: Population of GA (a) Formation of the impedance matrix and (b) tuning elements in a chromosome

B. Boundaries

In conventional GA, the initial population is produced randomly. This will greatly increase the searching time and impractical for the adaptive impedance tuning problem domain. In ITuneGA, the boundaries of initial population are defined based on available capacitance ranges of tunable components, as by (3). This technique applies to both discrete and continuous switching. Discrete switching utilises fixed capacitor array and on-off switches to configure different impedance states. The changes of the impedance are in discrete steps. For continuous switching, variable capacitors could be used. The changes of the impedance are in continuous manner. The potential solution will be rounded to the nearest impedance state for discrete switching. For continuous switching, the actual impedance will be based on the resolution of the actuating circuitry for the tunable devices.

$$X^N_{min} \leq \text{Initial population} \leq X^N_{max} \tag{3}$$

C. Formation of the susceptance matrix

Based on the topology in Figure 1(b), the arrays of the tunable capacitors encoded in the chromosomes will be transformed to the impedance, as given by Equation (4). The input impedance (Z_{in}) can be obtained by applying Equations (5) and (6) alternately for *M* number of tuning components. The Equations (4-6) are applied to all types of transmission line, including coaxial cable, microstrip and metal waveguides.

$$ZTune^M_{i,t+1} = 1/(2*\pi*f*C_{[1...M]}) \tag{4}$$

$$ZT_{i,t+1} = Z_{Load} // ZTune^M_{i,t+1} \tag{5}$$

$$Z_{in} = Z_0 \frac{ZT_{i,t+1} + j(Z_0 Del_i)}{Z_0 + jZT_{i,t+1} Del_i} \text{ with } Del_i = \tan\Delta\lambda_i \tag{6}$$

where Z_0 is system impedance (normally at 50 Ω), $ZT_{i,t+1}$ is the total branch impedances at each iteration, $ZTune^M_{i,t+1}$ is the tuning impedance based on *M* number of capacitors in *Pi*-network topology, Del_i is the radian of wavelength between tuning capacitors ($\Delta\lambda_i$)

D. Fitness value

VSWR is a measure of the degree of impedance mismatch. Fitness function of ITuneGA (*Fit*) is controlled by VSWR while VSWR is determined by Γ and Z_{in} , which are derived from the chromosome (X_i^N). Z_{in}, and far from the centre of the Smith chart, thus exhibits higher VSWR; while Z_{in}, which is closer to the coordinate of Smith chart has lower VSWR. In order to improve the searching efficiency in a complex impedance domain, we define a new searching strategy by Equations (7) and (8).

$$Fit = f\{VSWR\} * W^N_{i,t+1} \tag{7}$$

$$W_{i,t+1}^{N} = W_1 * D_{i,t+1}^{N} + W_2 * \delta_{i,t+1} + W_3 \quad (8)$$

where $W^{N}_{i,t+1}$ is the distance between chromosomes, i is the time of iteration, $D^{N}_{i,t+1}$ is the initial distance between chromosomes which makes the next $W^{N}_{i+1,t+1}$ keeps comparatively stable. $\delta_{i,t+1}$ is the distance between the previous and the current best chromosomes , and $W1$, $W2$ and W_3 are the weighting factors.

In this work, two point crossover has been selected.

E. Selection

At the beginning of evolution, there are larger distances among chromosomes and wider spread range. A higher fitness value is generated with a very high VSWR due to the location of Z_{in} ,which is far from the centre of the Smith chart. Thus, a better exploration to potential solutions is obtained. Crossover and mutation happen along the evolution. Crossover, a convergence operation, is intended to pull the population towards a local minimum. Mutation, a divergence operation, is intended to occasionally break one or more chromosomes of a population out of a local minimum and potentially discover a better minimum space. Toward the end of evolution, chromosomes in ITuneGA will have smaller spread range, and a relatively smaller VSWR will be obtained. However, the domains of adaptive impedance tuning network are almost nonlinear and multi peak values. In conventional GA, the algorithm might converge at this local optimum when all chromosomes search for the same optimal peak. By including the distance factor $W^{N}_{,i,t+1}$ which adjusts the distance among chromosomes, this keeps the chromosomes in ITuneGA search for different optimal peaks in the small defined region. Thus, a better exploitation to current smaller search area is achieved. Through this approach, we can gain a higher searching ability to explore complex impedance domain, and a higher ability of the exploitation to increase the convergency.

VI. RESULTS AND DISCUSSIONS

We demonstrate the effectiveness of the developed algorithm based on ITuneGA for an impedance tuner based on *Pi*-network with a wavelength ($\Delta\lambda_i$) of 30^0 between two tuning elements to match a mismatch antenna load of 7.4+j*13.2. The working frequency is at 2.45GHz. 100 chromosomes are used in the simulation. The algorithm stops as soon as the user-defined threshold for *Fit(n)* is reached (e.g., $|Fit(n)| \leq 1.1$) or the maximum number of iterations (i.e., 1000) is exceeded. Figure 5 shows Z_{in} before and after applying the ITuneGA in Smith chart. Comparison has made between the proposed ITuneGA and the conventional GA. The results show that ITuneGA outperforms conventional GA with its fast convergence time and high accuracy.

The developed ITuneGA has also been tested with *Pi*-network with four tuning elements. Convergence of ITuneGA based on real and imaginary parts of the input impedance over the number of iterations is presented in Figure 6. The real part of the input impedance is moved towards 50 Ω, while the imaginary part of the input impedance is moved towards 0 Ω. This value of the input impedance is closely matched with system impedance (Z_0 = 50 Ω), thus significantly reduce the reflected power.

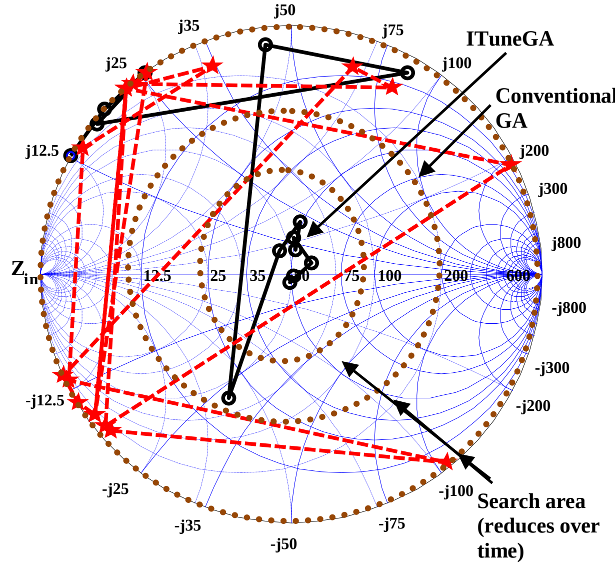


Figure 5: Convergence of ITuneGA and the conventional GA based on complex input impedances in Smith chart

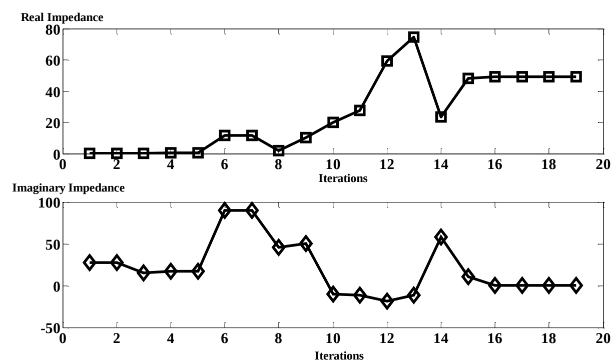


Figure 6: Convergence of ITuneGA based on real and imaginary parts of input impedance over number of iterations

The variations in four tuning elements over iterations are presented, as shown in Figure 7. The optimum sizes of tuning elements have been obtained at the 19th iteration. The convergence of the algorithm over iterations is presented in Figure 8. With the optimum sizes of tuning elements, the impedance mismatch at the network has successfully been reduced by having a low VSWR of 1.0352.

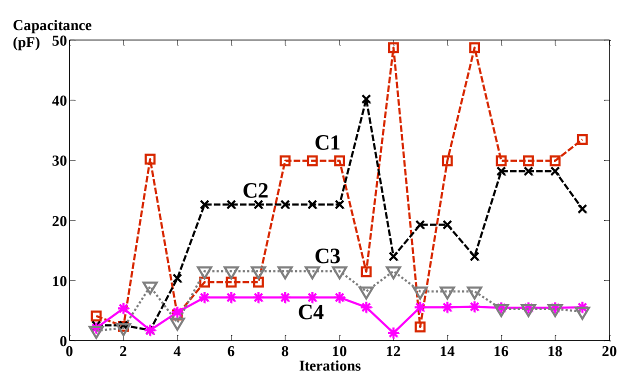


Figure 7: Tuning elements C1, C2, C3 and C4

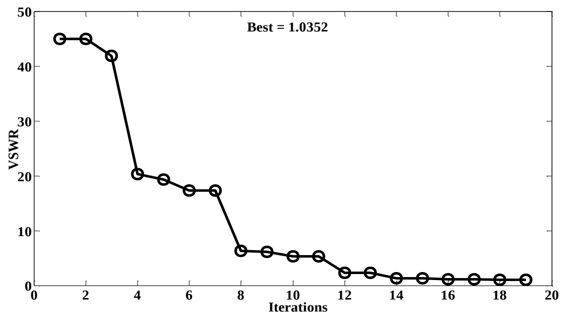


Figure 8: Convergence of ITuneGA based on VSWR over number of iterations for the impedance tuner with four tuning elements

Table 1 compares the average VSWR and CPU time for ITuneGA, conventional GA and LMS in 1000 runs based on two and four tuning elements in *Pi*-network for mismatches involving both real and imaginary part of Z_{Load} (15+j15.6) and solely the imaginary part of Z_{Load} (50+j15.6). LMS is based on the error signal generated by comparing the Z_{in} with the desired system impedance. While, the conventional GA is based on fitness function which controlled by VSWR. The tuning values need to be properly defined to avoid exceeding its boundary.

LMS shows a faster convergence speed compared to ITuneGA and the conventional GA. However, LMS is unable to converge when both real and imaginary parts are involved in the tuning process. ITuneGA achieves the best VSWR values, which are close to 1 (VSWR=1; no power reflection) for two and four tuning elements networks in all load conditions. Furthermore, ITuneGA significantly reduces the convergence time compared to the conventional GA by more than 40%.

Table 1: The average VSWR and CPU time for ITuneGA, conventional GA and LMS in 1000 runs based on 2 and 4 tuning elements in *Pi*-network for mismatches involving both real and imaginary part of Z_{Load} (15+j15.6) and solely the imaginary part of Z_{Load} (50+j15.6)

Adaptive Algorithm	No. of Tuning Elements	Elements in Z_{LOAD} to be Corrected	Average VSWR	CPU Time (ms)	Comments
ITuneGA	2	Imaginary only	1.0115	380.3	good convergence rate and robust
		Real & Imaginary	1.0249	397.2	
	4	Imaginary only	1.05	644.0	
		Real & Imaginary	1.0397	689.8	
Conventional GA	2	Imaginary only	1.2028	556.8	Slow CPU time
		Real & Imaginary	1.3921	544.6	
	4	Imaginary only	1.2250	965.9	
		Real & Imaginary	1.3981	973.2	
LMS	2	Imaginary only	1.0979	20.3	Unable to converge for the mismatches involving both real and imaginary parts
		Real & Imaginary	3.6866	20.4	
	4	Imaginary only	-	-	
		Real & Imaginary	-	-	

VII. Conclusions

For impedance matching networks, we have presented an adaptive impedance tuning algorithm (ITuneGA) which has faster convergence speed and accuracy than the existing algorithms, i.e. conventional Genetic Algorithm and LMS. The developed ITuneGA can intelligently increase diversity and escape from local optimum traps, enabling it to converge to better solutions. The effectiveness of the developed algorithm has also been verified by using *Pi*-networks that consist of two and four tuning components. The results show that mismatch antenna load has successfully converged to a 50Ω which matched with the system impedance. The developed ITuneGA significantly reduces the convergence time, by more than 40% compared to the conventional GA. The reduction in search time is important for achieving better link quality for next generation multi-band multi-mode mobile applications.

Acknowledgment

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