

Wideband Tuning of Impedance Matching for actual RF Networks using AQPSO

Yinxin¹, Tanyanghong*¹, Liaojiwang²

¹College of Electrical & Information Engineering, Hunan University, 410082, China

²Hunan College of Information

*Corresponding author, e-mail: tanyho@126.com

Abstract

An adaptive wideband impedance matching technique using a passive PI-network is presented in the paper on the basis of adaptive quantum particle swarm optimization algorithms (AQPSO), which avoiding the drawbacks of the standard particle swarm optimization (PSO) algorithm. The Wideband Tuning technique is for actual RF chips. So on-chip models for RF capacitors and inductors are considered. And the effects of the parasitic component loss in the PI-network are analyzed. Then the circuit is simplified according to the sensitivities of the elements. Therefore, the computational complexity is dramatically reduced. Finally, the AQPSO algorithm is adopted to maximize the power transmission efficiency. Simulation results show that the proposed tuning technique can achieve good accuracy of impedance matching and load power. The reflection coefficient and VSWR obtained are also satisfactory. Moreover, the proposed method can be useful for software defined radio systems using a single antenna for multiple mobile and wireless bands.

Keywords: impedance matching, passive PI-network, particle swarm optimization, parasitic component, AQPSO

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1. Introduction

Today's mobile and wireless communication devices are used in almost all imaginable environments, such as in cell phone, in cars, in talking position near the head. The environment of the antenna and the resulting field distribution around it has unfortunately an eminent impact on its impedance [1]. And the mismatch between antenna and source/transmitter reduces its power efficiency, linearity and lowers the power of the input/output signal. Moreover, maximum power is expected to transmit to the antenna to achieve maximum transmission efficiency. So the goal of obtaining fast antenna tuning systems, which are capable of offering impedance matching (IM) with changing load and environmental aspects, has become increasingly significant. The lowpass Pi and lowpass T circuits, as the most popular impedance matching configurations are characterized by their simple structures, wide range of load impedance accommodations and high harmonic rejection capabilities [2].

Various communication standards have also been developed to contain a variety of applications at different frequency bands, such as cellular communications at 900 and 1800MHz, global positioning system (GPS) at 1.2 and 1.5GHz, and Bluetooth and WiFi at 2.4 and 5.2GHz. Due to high operation frequency, as well as low voltage and small size trend, impedance matching network are very difficult to design. To put them on to silicon chip has proved even more difficult in view of non-idealities in fabrication technology and parasitic effects at high frequency. Thus the impedance matching networks will suffer from the power loss. Thus it is crucial to be able to evaluate such power loss in the design and analysis of matching networks for budgeting system power.

Mismatch of the antenna impedance suffers significant degeneration of the power efficiency of the radio link. Automatic matching networks are therefore developed to match any change in antenna impedance in many RF applications [3-18]. Single frequency impedance matching methods are widely applicable in many areas such as power amplifiers and antenna tuning systems. Automatic tuning methods have been investigated using genetic method [3]. A particle swarm optimization (PSO) based algorithms have been used in [4], [5-7]. [8] proposed a hierarchical genetic algorithm. However, its ability is limited to improve automatic matching

network nodal quality factors and increase the overall matching efficiency. It is found that the proposed tuning methods so far are all single frequency based mainly at HF range. The channels which have very narrow signal bandwidth, thus very high Q at high frequencies can be tuned to, by sweeping the frequency range of interest. They involve switching between different frequencies, channels and bands/standards, as may be needed. Moreover, these approaches are all based on the ideal matching networks. That is, the parasitic-aware effects of the capacitors and inductors in the matching networks are not considered. And the parasitic-aware parameters strongly affect the power efficiency of the radio [17].

Here we consider a wideband tuning issue and propose a method based on an adaptive quantum particle swarm optimization algorithm (AQPSO), which is a combination of an improved Adaptive particle swarm optimization algorithm (APSO) with a Quantum Particle Swarm Optimization (QPSO). By sharing the two returned extreme values of the particles from APSO and QPSO, the proposed method enables to adaptively search their optimum solutions in parallel. Using this method, the impedance matching networks can be tuned to cover a band of frequencies, for all channels of both uplink and downlink, and indeed multi-bands of several standards.

In this paper, we describe the impedance matching network, analyze on-chip inductor model's sensitivity and simplify impedance matching structure in Section 2. The wideband impedance tuning method using AQPSO is proposed in Section 3. Simulations and results are presented for GSM, UMTS and both in Section 4. Conclusions are drawn in Section 5.

2. Impedance Matching Network Analysis

The major purpose of impedance matching network is to maximize power transmission efficiency if load impedances and channels change. Figure 1 shows the tunable matching network structure. The antenna links together the signal source with power amplifier through the tunable matching network. When antenna impedance or frequency channel change, the central processing unit gets information about antenna impedance and band of frequency through the sensor. And then processing unit use its internal AQPSO algorithm to compute the element parameters in impedance matching network and through the execution unit adjust the value of L, C1 and C2.

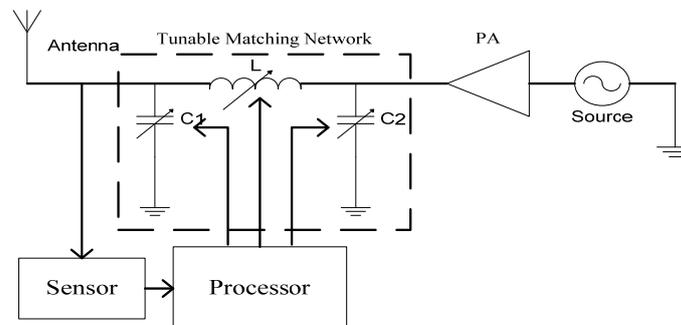


Figure 1. Tunable Matching Network Structure

Let us consider the parasitic-aware effect of the inductor at first. (Kiyong Choi, David J., Allstot 2006; Gupta, R., Ballweber B.M. 2001) presents an inductor model for use in parasitic-aware synthesis. Parasitic-aware modeling begins with the design and fabrication of several inductors that span a range of inductances with adequate quality factor and self-resonance frequency values for the anticipated applications. Figure 2 shows an accurate parametric on-chip inductor model. Each segment is modeled using a lumped equivalent circuit comprising a self-inductance, a series resistance equal to the dc resistance of the metal segment, a shunt capacitance representing the capacitive coupling between the metal forming the segment and the substrate, an effective substrate loss resistance computed simply as a lateral spreading resistance.

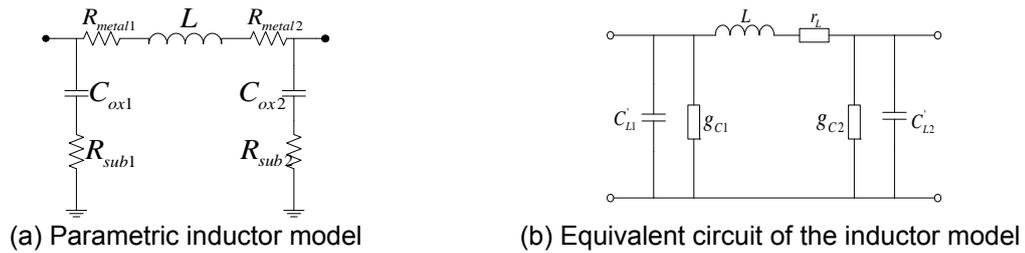


Figure 2. Parametric Model and its Equivalent Circuit of a Planar Inductor

Figure 2(a) shows a parametric planar inductor model, where R_{metal} , C_{ox1} , C_{ox2} , R_{sub} are functions of L over a desired range of inductances. The floating inductor of the range is from 1nH to 18nH:

$$R_{metal} = -0.0278L^2 + 1.741L + 2.3402 \tag{1}$$

$$C_{ox1} = C_{ox2} = -0.0005L^2 + 0.0307L + 0.0468 \tag{2}$$

$$R_{sub} = -0.0894L + 32.151 + 3.5064/L \tag{3}$$

Where L is in nH, C_{ox1} and C_{ox2} are in pF, and R_{metal} and R_{sub} are in ohms.

The circuit may be converted into Figure 2(b) through Equation (4), (5) by applying series to parallel conversion.

$$C'_{L1} = \frac{C_{ox1}}{1 + \omega^2 C_{ox1}^2 R_{sub}^2} \tag{4}$$

$$g_{C1} = \frac{\omega^2 C_{ox1}^2 R_{sub}}{1 + \omega^2 C_{ox1}^2 R_{sub}^2} \tag{5}$$

So the Impedance matching network is shown in Figure 3, if the parasitic parameters of the inductor are considered. Let $C1'=C1+CL'$, $C2'=C2+CL'$, the circuit is transformed into Figure 4. In order to consider the parasitic-aware effect of the inductor, by calculating the sensitivities of Z_{in} and P_L to s , where $s=\{r_L, g_{c1}, g_{c2}\}$, we get:

$$\frac{\partial Z_{in}}{\partial r_L} \gg \frac{\partial Z_{in}}{\partial g_{C2}}, \frac{\partial Z_{in}}{\partial r_L} \gg \frac{\partial Z_{in}}{\partial g_{C1}} \frac{\partial P_L}{\partial r_L} \gg \frac{\partial P_L}{\partial g_{C1}}, \frac{\partial P_L}{\partial r_L} \gg \frac{\partial P_L}{\partial g_{C2}} \tag{6}$$

Therefore, the effect of g_{c1} and g_{c2} to input impedance and power is far less than that of r_L . It is appropriate to ignore g_{c1} and g_{c2} . So the circuit can be simplified as Figure 5.

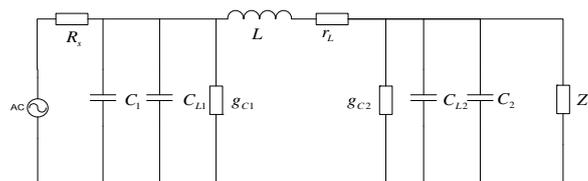


Figure 3. Impedance Matching Circuit Considering Parasitic Parameters of the Inductor

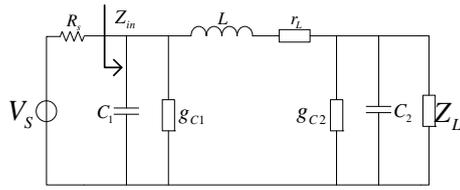


Figure 4. Equivalent Circuit of Figure 3

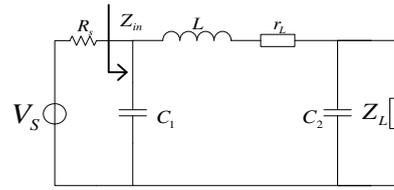


Figure 5. The Simplified Circuit of Figure 3

Now consider the parasitic-aware effect of the capacitors. In Figure 3, the parallel arm loss conductance of the inductor is treated as the parasitic loss conductance of the capacitors, say g_{c1} and g_{c2} . And the parasitic capacitance, say CL_1 and CL_2 can be absorbed by C_1 and C_2 by letting $C_1' = C_1 + CL_1$, $C_2' = C_2 + CL_2$, thus the effects of CL can be eliminated. Loss g_{cL} is in parallel with C_1 and C_2 and therefore can be treated in the same way as g_{c1} and g_{c2} . Therefore the formulas proposed are now applicable to both inductor and capacitor models.

3. AQPSO Method for Wideband Impedance Tuning

PSO is a population-based stochastic optimization technique developed in (Kennedy J, Eberhart R 1995). It is a stochastic optimization method based on swarm intelligence. The fundamental idea is that the optimal can be found through cooperation and information sharing among individuals in the swarm. Through cooperation and competition among the population, population-based optimization approaches often can find good solutions efficiently and effectively. However, it may easily trap into local optimal points and may difficultly obtain exact solutions at the late of the iteration.

To overcome the weakness, some researchers have employed methods with adaptive parameters and combined quantum model. An adaptive mode adjusts the parameters according to the feedback information, such as fuzzy adaptive inertia weight (Y. Shi, R. Eberhart 2001). A combined quantum model is presented in (Sun J, Feng B, Xu WB 2004), where particles are changed according to quantum movement rules, such as particles having quantum behavior. In this paper, a new parallel adaptive quantum particle swarm optimization algorithm is proposed. By sharing the two extreme of the particles, the proposed method adaptively searches their optimum solutions in parallel. It combines the optimizations of an improved adaptive PSO (APSO) with a quantum Particle Swarm Optimization (QPSO). The APSO thread and the QPSO thread operate in parallel.

3.1. APSO Thread.

Standard particle swarm optimization might undergo an undesired process of diversity loss. Some particles become inactively while lost both of the global and local search capability in the next generations. The lost of global and local search capability means that particles will be only moving within a quite small space, which will be occurs when its location and pbest is close to gbest (pbest is the optimal position of the particle until now, gbest represent the past optimal position of the swarm) and its velocity is close to zero. To overcome this problem, the adaptive particle swarm uses newly nonlinear inertia weights and acceleration coefficients to control the velocity of particles and avoids clustering of particles and maintains diversity of population in the search space.

The adaptive particle swarm optimization consists of, at each time step, changing the velocity and location of each particle toward its pbest and gbest locations according to the Equation (7) and (8), respectively:

$$V_{i+1} = w * V_i + c_1 * rand() * (pbest - x_i) + c_2 * rand() * (gbest - x_i) \quad (7)$$

$$x_{i+1} = x_i + V_i \quad (8)$$

Where the location of the i th particle is represented as x_i . The best previous position of the i th particle is recorded and represented as p_{best} . The index of the best p_{best} among all the particles is represented by the symbol g_{best} . The velocity for the i th particle is represented as V_i . The $\text{rand}()$ is a random at interval $[0,1]$ with uniformly distribution. The first part of Equation (7) represents the previous velocity, which provides the necessary momentum for particles to fly across the search space. The second part is known as the “cognitive” component, which represents the personal thinking of each particle. This component encourages the particles to fly toward their own best position found so far. The third part is known as the “social” component, which represents the collaborative effect of the particles in finding the global optimum. This component always pulls the particles toward the global best position the whole swarm found so far.

The inertia weights are updated as:

$$w = (w_{\max} - w_{\min}) / \left(1 + e^{\left(\frac{20G}{G_{\max}} - 10 \right)} \right) + w_{\min} \quad (9)$$

Where w_{\max} and w_{\min} are the initial and final values of the inertia weights, respectively, G is the current iteration number and G_{\max} is the maximum number of allowable iterations.

The acceleration coefficients are adjusted nonlinearly as follows:

$$c_1 = (c_{1f} - c_{1s}) * \left(\frac{G}{G_{\max}} \right)^3 + c_{1s}, c_2 = (c_{2f} - c_{2s}) * \left(\frac{G}{G_{\max}} \right)^3 + c_{2s} \quad (10)$$

Where c_{1s} and c_{1f} are the initial and final values of the acceleration coefficient c_1 , c_{2s} and c_{2f} are the initial and final values of the acceleration coefficient c_2 .

This strategy implies that at the beginning of the search the cognitive component has more weight than the social component, so the particles can search rapidly and widely in the whole space, while at the latter of search, the social component plays more important role to make particles converge to the global optima.

3.2. QPSO Thread

Quantum Particle Swarm Optimization algorithm (QPSO) is proposed in 2004. In classical PSO, a particle is stated by its position vector X_i and velocity vector V_i , which determine the trajectory of the particle. The movement of the particle along the determined trajectory follows Newtonian mechanics. However, in case of quantum mechanics the term trajectory is meaningless, because X_i and V_i of a particle cannot be determined simultaneously according to uncertainty principle. Therefore, if individual particles in a PSO system have quantum behavior, the performance of PSO will be far from that of classical PSO. In the quantum model of a PSO, the state of a particle is depicted by wave function $\varphi(x,t)$, instead of position and velocity. The dynamic behavior of the particle is widely divergent from that of the particle in traditional PSO systems in that the exact values of X_i and V_i cannot be determined simultaneously. In this context, the probability of the particle's appearing in position X_i from probability density function $|\varphi(x,t)|^2$, the form of which depends on the potential field in which the particle lies. Employing the Monte Carlo method, the particles move according to the following iterative Equation (11):

$$X(t) = P \pm \ln(1/u) * L / 2 \quad (11)$$

Where u is random number with uniformly distribution, L is determined from $L(t+1) = 2\beta |mbest - X(t)|$, the parameter β is called Contraction-Expansion (CE) Coefficient, which can be tuned to control the convergence speed of the particle. $\beta = (1-0.5) * \left(\frac{G_{\max} - G}{G_{\max}} \right) + 0.5$. $mbest$ called Mean Best Position, is defined as the mean of the p_{best} positions of all particles. That is :

$$mbest = 1/M * (\sum_{i=1}^M pbest_{i1}, \sum_{i=1}^M pbest_{i2}, \dots, \sum_{i=1}^M pbest_{iDim}) \quad (12)$$

Where M is the number of particles of the population, Dim is the dimension of the particles, pbest_{iDim} is best position of particles. Convergence of the PSO algorithm may be achieved if each particle converges to its local attractor, P defined at the coordinates:

$$P = \varphi * pbest + (1 - \varphi) * gbest \quad (13)$$

$$X_{id}(t+1) = P \pm \beta * |mbest_d - X_{id}(t)| * \ln(1/u) \quad (14)$$

φ is random number uniformly distributed on (0,1), pbest and gbest present the best particle position and the best position of particles in the population.

Generally, the value of each component in X_{id} can be clamped to the range that distribute in feasible zone around border to control excessive roaming of particle outside the search space. The method is given as follow:

$$\begin{aligned} \text{If } X_{id} > X_{max} & \quad X_{id} = X_{max} - c * (X_{id} - X_{max}) * \text{rand}() & \quad \text{or} \\ \text{If } X_{id} < -X_{max} & \quad X_{id} = -X_{max} - c * (X_{id} + X_{max}) * \text{rand}() & \quad (15) \end{aligned}$$

The value of c is applied here to adjust the range of the particles, and the X_{max} is the maximum moving distance.

As shown in Figure 6, the flow of the AQPSO algorithm is shown in Figure 6. Explained as follows:

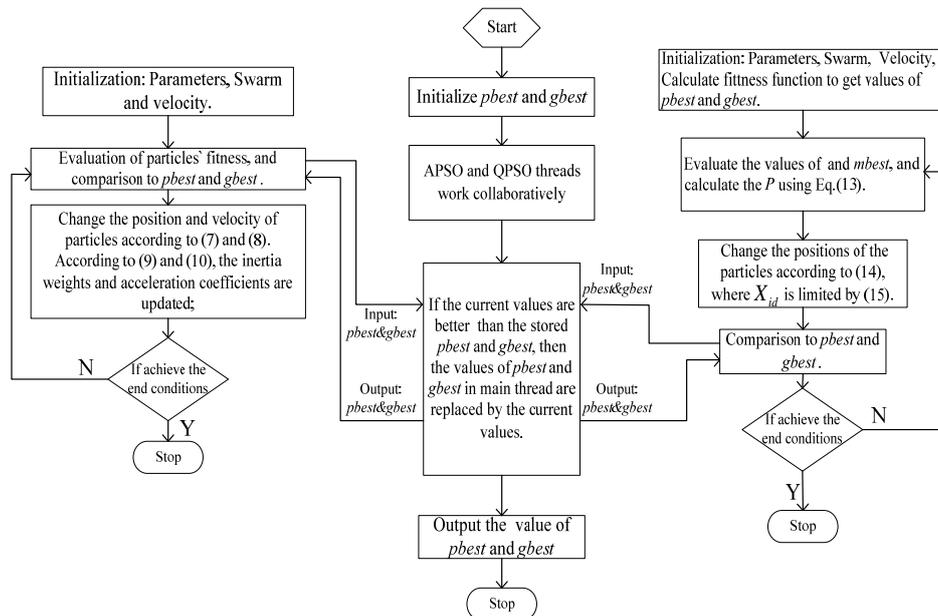


Figure 6. AQPSO Flow Chart

Step 1: The initial parameters are generated at the beginning of program.

Step 2: APSO and QPSO threads work collaboratively. The position and velocity of particles are randomly distributed in APSO thread. QPSO evaluate the fitness for each particle to get values of pbest and gbest.

Step 3: In APSO thread, the fitness function value of each particle is calculated to determine the gbest position. The current values of pbest and gbest are compared with the corresponding returned values from the main thread. If the current values are better than the

stored pbest and gbest, then the values of pbest and gbest in main thread are replaced by the current values. In QPSO thread, the values of β and mbest is evaluate, and P is found using Equation (13).

Step 4: APSO calls pbest and gbest in main thread to change the position and velocity of particles according to Equation (7) and (8). According to Equation (9) and (10), the inertia weights and acceleration coefficients are updated; QPSO thread change the positions of the particles according to Equation (14), where Xid is limited by Equation (15).

Step 5: The end of each generation, the terminal condition is examined and the process is terminated when the condition is satisfied in APSO. When the terminal condition is not satisfied the process progresses into the next step. The fitness function of each particle is determined to obtain the gbest position in QPSO. Comparing the current values of pbest and gbest with the returned values from the main thread, and the better pbest and gbest are kept for next iteration. Otherwise, the values of pbest and gbest from main thread are updated.

Step 6: All threads are examined at the end of each generation. If the evolutionary cycle or target value is completed, the AQPSO is terminated and outputs the pbest and gbest. If not, turn to Step 3.

4. Experiment

4.1. Fitness Function

The simplified PI-network is showed in Figure 5. Here, Vs is the signal source, Rs is the transmission impedance (typically 50 ohms), rL is Rmetal in Figure 2, and ZL=R+jX represents the load impedance (e.g. antenna input impedance), Zin represents the input impedance and Zeq is the output impedance.

We may easily obtain that the input power would be:

$$P_{in} = \frac{|V_{in}|^2}{R_{in}} = 4 \frac{R_s}{R_{in}} \left| \frac{Z_{in}}{Z_{in} + R_s} \right|^2 P_{ava} \quad (16)$$

Where $P_{ava} = |V_s|^2 / (4R_s)$ is the maximum powers, and Vs is the amplitude of the source voltage. Let Γ_s be the reflection coefficient, we have:

$$\Gamma_s = (R_s - Z_{in}) / (R_s + Z_{in}) \quad (17)$$

Voltage standing wave ratio (VSWR) can be written as:

$$VSWR = (1 - |\Gamma_s|) / (1 + |\Gamma_s|) \quad (18)$$

The cost function can be chosen as:

$$f(\omega) = \sum_{i=1}^M f_i(\omega) = |VSWR_i - VSWR_0| \quad (19)$$

Where $f_i(\omega) = |VSWR_i - VSWR_0|$, M is the total number of the sample points over the considered frequency range. VSWR0 is the target value of the voltage standing wave ratio, which is ideally 1. Our aim is to minimize the cost function fitness. As $f(w)$ is a highly nonlinear function of the components C1, C2 and L, a direct minimization of the cost function is a very difficult task.

4.2. Simulation Results

Several examples have been calculated to demonstrate the performance of the proposed approach. The examples showed wideband impedance matching technique compared to never using any technique.

Example 1: GSM-1800 uses 1710–1785MHz for uplink and 1805–1880MHz for downlink. Here we consider the frequency range/band from 1.71GHz to 1.88GHz. The source resistance is 50Ω . The load impedance is capacitive, $Z_{load}=50-j75\Omega$. 100 points are sampled in the frequency range.

The obtained matching component values are $C_1=0.020151\text{pF}$, $C_2=0.018097\text{pF}$, and $L=5.08351\text{nH}$. The curves of load power and reflection coefficient with IM, load power and reflection coefficient without IM are shown in Figure 7. The average values of load power and reflection coefficient with impedance matching (IM) are 3.9797mw and 0.17895 . While without IM, their values are 3.2mw and 0.59999 , respectively. Thus without the proposed technique, the power transmission efficiency has been increased by 19.59%.

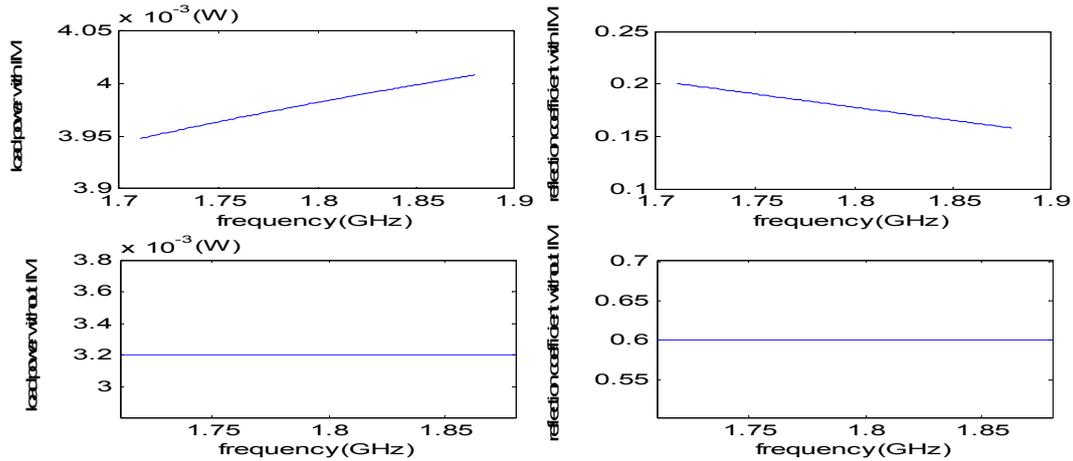


Figure 7. Load power, Reflection Coefficient for GSM-1800MHz

Example 2: UMTS specifies the bands 1900-2025MHz and 2110-2200MHz for 3G transmission. Here we consider the band from 1.9 to 2.025GHz (we will consider even wider band to include 2.11-2.2GHz in Example 3). The source resistance is 50Ω . The load impedance is resistive, $Z_{load}=200\Omega$. A set of 100 sampled points are considered in the test. The obtained matching component values are $C_1=0.33560\text{pF}$, $C_2=0.62876\text{pF}$, and $L=6.65031\text{nH}$. The curves of load power and reflection coefficient with IM, load power and reflection coefficient without IM are shown in Figure 8.

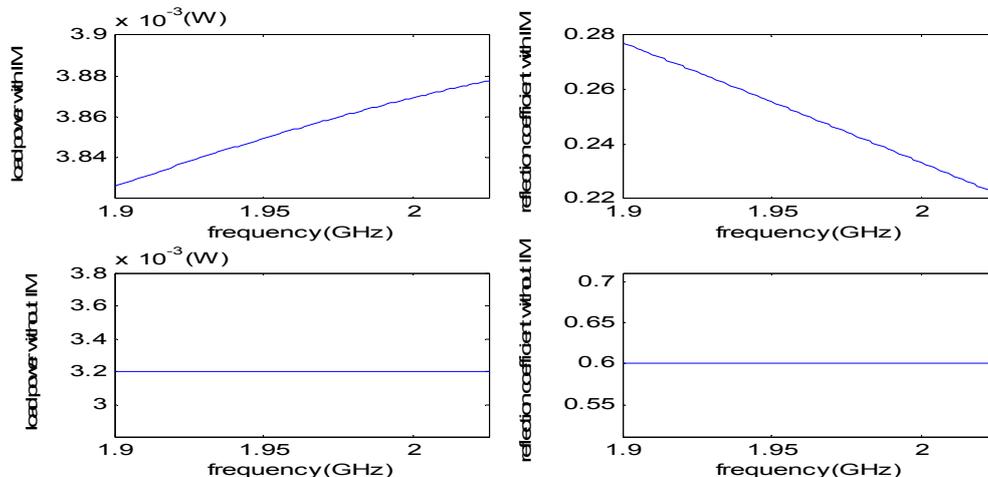


Figure 8. Load power, Reflection Coefficient for UMTS

With the proposed IM unit, the average values of load power and reflection coefficient are increased from 3.2000mw and 0.6001 to 3.85387mw and 0.24985. The proposed technique has enhanced power transmission efficiency by 16.96%.

Example 3: We now consider dual modes GSM-1800 and UMTS. The frequency ranges from 1.7 to 2.2GHz for the dual standards. The source resistance is 50Ω. The load impedance is inductive, $Z_{load}=60+j120\Omega$. A set of 500 sampled points are considered in this experiment. The obtained matching component values are $C1=0.380467pF$, $C2=0.956331pF$, and $L=3.18740nH$. The curves of load power and reflection coefficient with IM, load power and reflection coefficient without IM are shown in Figure 9.

The percentage of power transmission efficiency has enhanced 38.02% with our IM technique form 2.2641mw to 3.6535mw.

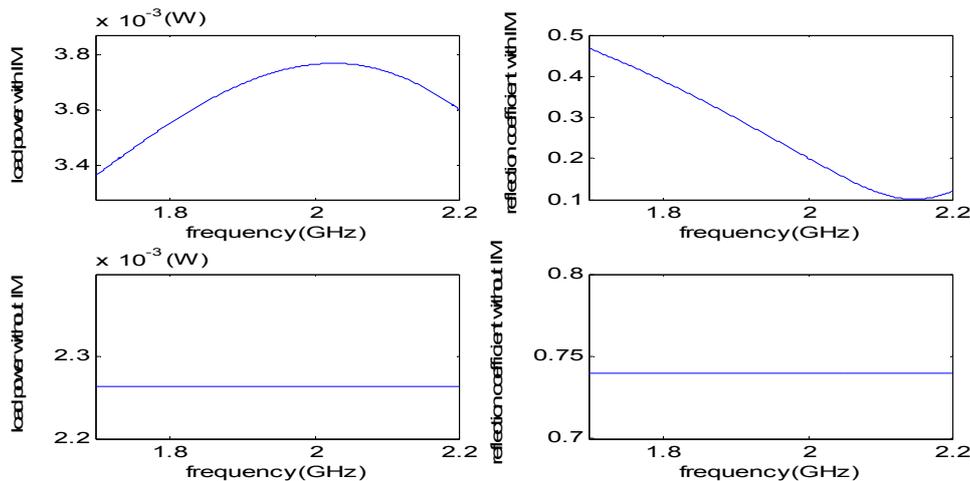


Figure 9. Load power, Reflection Coefficient for UMTS

Figure 7 through Figure 9 indicate that the value of load power is close to the maximum power with our IM unit. Through the proposed technique, we can achieve satisfactory transmission efficiency and reflection coefficient. So the proposed impedance matching network is capable of offering impedance matching with changing load and channels.

In addition, in order to assessment the proposed IM unit for actual RF Networks, we compare the returned results by applying the simplified model and the ideal model. The ideal model presents the model without considering any parasitic-aware effects of the inductor and the capacitors in the IM unit, while the simplified model is shown in Figure 5. The results can be seen in Table 1.

Table 1. The Power Loss Comparison of Simplified Model and Ideal Model

Power loss(w)	(GHz)	1.71-1.88	1.9-2.025	1.7-2.2
	(Ω)	ZL=50-10j	ZL=20	ZL=60
Simplified model	Best	5.3953E-04	1.1261E-03	4.3527E-04
	Worst	5.4973E-04	1.1543E-03	5.0555E-04
	Mean	5.4463E-04	1.1401E-03	4.6930E-04
Ideal model	Best	1.6957E-03	1.1639E-03	5.2793E-04
	Worst	1.7149E-03	1.2002E-03	5.4916E-04
	Mean	1.7051E-03	1.1802E-03	5.3672E-04

Table 1 shows that the power loss of the simplified model is less than that of the ideal model for GSM, UMTS and dual standards from 1.7 to 2.2GHz. The power losses of the obtained simplified model over the frequency range are 5.4463E-04, 1.1401E-03 and 4.6930E-

04, respectively. However, the corresponding power losses of the ideal model are $1.7051E-03$, $1.1802E-03$ and $5.3672E-04$. The power transferred to load grows by an average of 28%.

Simulation results show that the proposed wideband impedance matching technique can improve the efficiency of load power, control reflection coefficient in a satisfactory scope. So the proposed adaptive tuning technique can achieve good accuracy of impedance matching and load power for different antenna impedances. The reflection coefficient also satisfies the needs of the project. Moreover, the proposed method can be useful for software defined radio systems using a single antenna for multiple mobile and wireless bands.

4. Conclusion

This paper presents an adaptive wideband impedance tuning technique for multi-standard mobile communications. The on-chip models for RF capacitors and inductors are considered, and the circuit is simplified according to the sensitivities of the elements. Therefore, the computational complexity is dramatically reduced. AQPSO is chosen to improve impedance matching. Examples are given for GSM, UMTS and dual standards with three different antenna impedances. The frequency range for the dual standards is from 1.7 to 2.2GHz. Simulation results show good accuracy of input impedance matching and power transfer. The reflection coefficient and VSWR are also satisfactory. The proposed tuning method may also be suitable for even wider range of frequencies to cover other wireless standards.

Acknowledgement

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