Optimization of Thermodynamic Cycles for Gas Turbines Using Genetic Algorithms

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ABSTRACT

The Darwin's theory of natural evolution is being used in the last one decade for optimization of many engineering systems in the name of genetic algorithms. In the present paper, genetic algorithms are used for the optimization of the gas turbine cycles. Based on thermodynamic consideration of a gas turbine plant, the pressure ratio is optimized with genetic algorithms for maximum efficiency or maximum net power density. In addition to the pressure ratio, component efficiencies and maximum cycle temperature are treated as independent (decision) variables. The effects of the independent variables on the pressure ratio are also determined. Economics are combined with thermodynamics to formulate a thermoeconomic optimization problem. The results obtained by genetic algorithms are compared with the numerical results to demonstrate the capability of genetic algorithms in carrying out an optimization of thermodynamic cycles for gas turbines.

Keywords: gas turbine cycles; genetic algorithms; thermodynamic optimization; thermoeconomic optimization

NOMENCLATURE

b_e	specific fuel consumption: $b_e = \dot{m}_f / \dot{W}$
c_f	price of fuel
c_p	specific heat capacity
c_{r1}	cost parameters
E_f	exergy flow rate of fuel: $\dot{E}_f = \dot{m}_f \dot{\varepsilon}_f$
H_f	energy flow rate of fuel: $\dot{H}_f = \dot{m}_f H_u$
H_u	lower heating value of fuel
$\dot{I}$	total irreversibility rate
k	as defined by equation (1)
$\dot{m}$	mass flow rate
P	pressure
r_B	combustor pressure ratio: $r_B = P_3/P_2$
r_C	compressor pressure ratio: $r_C = P_2/P_1$
r_T	turbine pressure ratio: $r_T = P_3/P_4$
t	time of operation per year
T	temperature
w	non dimensional net power density
x	vector of decision variable
$\dot{W}$	net power output
Z	total annual cost of owning and operating the system

Greek letters

γ	specific heat ratio: $\gamma = c_p/c_v$
ε_f	specific exergy of fuel
ζ	second-law (exergetic) efficiency of the system
η	isentropic efficiency
η_∞	polytropic efficiency
η_{th}	thermal efficiency of the system
τ_i	non dimensional temperature: $\tau_i = T_i/T_1$
φ	ε_f/H_u

Subscripts

a air
e exit
f fuel
C compressor
B combustor
T turbine

Superscripts

* optimum value

Overmark

$\dot{}$ per unit time

1.0 INTRODUCTION

In the vast variety of engineering systems nowadays, there is a need to ensure that a given system is performing at the optimal level. This is necessary in many engineering applications since efficiency means cost saved and performance maximized. This is the preferred operating condition for any system and also an important criterion to be considered at the design level of any engineering system nowadays.

Much work has been done in optimization of engineering systems and most of the optimizations are carried out through numerical methods such as non-linear programming method and calculus-based method. One of the disadvantages of optimizing an engineering system by these methods is that it is very lengthy and complicated, and thus takes up a substantial amount of computing time, with considerable inaccuracies for certain cases. Inaccuracies are in the sense that, most of these methods use the principle of *hill climbing* by determination of gradients, and therefore if the given function has more than one local maximum, optimization with these methods may produce the answer of the local maximum instead of the global maximum [1]. This is where genetic algorithms (GAs) come into picture. GA is a robust search tool based on natural evolution of genetics. Optimization with GA will always produce the global maximum of a given function. This present work will introduce GA as another alternative tool that can be utilized to carry out optimization process of a given engineering system. Azid et. al. [2,3] have applied GA for solving a number of truss problems with only support and load positions specified in terms of topology and geometric optimization. Jeevan et. al. [4] has solved a PCB component placement problem using GA.

Many power generating plant in the energy sector still depend on system based on gas turbines. Among these are plants such as combined cycle cogeneration plants and the nuclear high temperature gas-cooled reactor. In many instances, attempts are always made to optimize the design and performance of these plants through dynamic modeling and simulation [5,6]. Frangopoulos has in his work, carried out thermodynamic and thermoeconomic optimization of a simple gas turbine plant using non-linear programming method. In addition, a sensitivity analysis of the optimal solution has also been carried out [7]. Based on Frangopoulos' work, GA will be applied to a simple gas turbine plant and optimization will be carried out based on objective functions derived purely on optimal thermodynamic design consideration. The analysis will involve the determination of decision variables and how these variables affect the objective function. The second part of this paper will deal with thermoeconomic optimization where economic considerations are combined with thermodynamic considerations.

2.0 GENETIC ALGORITHMS (GAs)

Prof. John Holland first invented Genetic Algorithm (GA) at the University of Michigan in 1975. Subsequently it has been made widely popular by Prof. David Goldberg at the University of Illinois. The original GA and its many variants, collectively known as genetic algorithms, are computational procedures that mimic the natural process of evolution. GAs are adaptive search methods based on Darwinian principles of natural selection, survival of the fittest and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. As in human genetics, GAs exploits the fittest traits of old individuals to create a new generation of artificial creatures (strings). With each generation, a better population of individuals is created to replace the old population. Based on these principles, genetic algorithms are developed as a search tool that efficiently exploits historical information to speculate on new search points with expected improved performance.

All genetic algorithms work on a population of individuals. Each individual in the population is called a string or chromosome, each representing a possible solution to a given problem. These individuals are then subjected to a series of evolution processes before they are evaluated and given a fitness score. The evolution processes involved in genetic algorithms are the selection process and the recombination process. Highly fit individuals are selected from the population for reproduction. Crossover is the main operator used for reproduction. It combines portions of two parents to create two new individuals, called offspring, which inherit a combination of the features of the parents. Mutation is occasionally introduced to individuals, where a single allele in a chromosome is changed randomly. The crossover process and the mutation process of two 8-bit genomes are shown in Fig. 1 and Fig. 2 respectively.

"Take in Figure 1"

"Take in Figure 2"

These two processes produce new individuals that will become a new population of solutions for the next generation. Members of the population with a low fitness score will be discarded and are unlikely to be selected for the next evolution process. The entire process of evaluation and reproduction then continues until either the population converges to an optimal solution for the problem or the genetic algorithm has run for a specific number of generations.

When GA is implemented, it is usually done in a manner that involves the following cycle:

Step 1 Generate a population randomly.

Step 2 Evaluate the fitness of all of the individuals in the population.

Step 3 Select the individuals with the best fitness score.

Step 4 Is stopping criteria fulfilled?

No, proceed to **Step 5.**

Yes, display the results.

Step 5 Crossover and mutation operations are conducted on the selected individuals to produce new population of individuals.

Step 6 Discard the old population and proceed to **Step 2** using the new population.

One cycle of this loop is referred to as a generation. We do not see this punctuated behavior of a population in nature as a whole, but it is a convenient implementation model. The first generation (generation 0) of this process operates on a randomly generated population of individuals or parents. From there on, the genetic algorithm operates to improve the fitness of the population.

3.0 THERMODYNAMIC DESIGN OPTIMIZATION

A study in thermodynamic design optimization of a simple gas turbine plant has been done by Frangopoulos [7] using non-linear programming method. A simple gas turbine cycle is shown in Fig. 3.

"Take in Figure 3"

It is assumed that the system operates at steady state, the power output, $\dot{W}$, is known, and there are no thermal and mechanical losses. It is also sufficiently accurate to assume that the working medium is an ideal gas with the following fixed values of c_p and γ for the compression and expansion process respectively:

air:	$c_{pa} = 1.005$ kJ/kg.K,	$\gamma_a = 1.40$
combustion gases:	$c_{pg} = 1.148$ kJ/kg.K,	$\gamma_g = 1.333$

For convenience, k_a and k_g is introduced as:

$$k_a = \frac{\gamma_a - 1}{\gamma_a}, \qquad k_g = \frac{\gamma_g - 1}{\gamma_g} \qquad (1)$$

3.1 Objective Functions

With reference to the work done by Frangopoulos, the same objective functions are used for optimization with GA. The following objective functions are examined under pure thermodynamic consideration:

(a) maximization of the cycle thermal efficiency, η_{th};

(b) minimization of the fuel consumption, $\dot{H}_f$;

(c) maximization of the net power density (also called specific power), $\dot{W} / \dot{m}_a$;

(d) minimization of the total irreversibility rate of the system, $\dot{I}$;

(e) maximization of the second-law efficiency of the system, ζ.

The thermal efficiency of the cycle is

$$\eta_{th} = \frac{\dot{W}}{\dot{H}_f} = \frac{\dot{W}}{\dot{m}_f H_u} \tag{2}$$

Because of the assumption of constant $\dot{W}$, the objectives (a) and (b) are equivalent. The second-law (or exergetic) efficiency of the cycle is

$$\zeta = \frac{\dot{W}}{\dot{E}_f} = \frac{\dot{W}}{\dot{W} + \dot{I}} \tag{3}$$

For constant $\dot{W}$, objectives (d) and (e) are equivalent. It can be written as

$$\zeta = \frac{\dot{W}}{\dot{m}_f \varepsilon_f} = \frac{\dot{W}}{\dot{m}_f H_u \dfrac{\varepsilon_f}{H_u}} = \frac{\eta_{th}}{\varphi} \tag{4}$$

where φ is constant for each specific fuel [8]. Hence, objectives (a) and (e) are equivalent. In conclusion, the five thermodynamic objectives mentioned above, reduces to only two different optimization problems, which will be studied in the following.

3.2 Maximization of the Cycle Efficiency

Maximizing the cycle efficiency is equivalent to minimizing the fuel consumption, minimizing the total irreversibility rate and maximizing the second-law efficiency of the system. With the definition of equation (2), the objective function can be shown as

$$\dot{m}_a c_{pa} T_1 (r_C^{k_a/\eta_{\infty C}} - 1) \le (\dot{m}_a + \dot{m}_f) c_{pg} T_3 \left[1 - (r_B r_C)^{-k_g \eta_{\infty T}}\right] \tag{13}$$

The equality in equation (13) applies for $r_c = r_{c,\,max}$, which gives

$$(r_{C,\max}^{k_a/\eta_{\infty C}} - 1)[1 - (r_B r_{C,\max})^{-k_g/\eta_{\infty T}}]^{-1} = (1+f)\tau_3 c_{pg} / c_{pa} \tag{14}$$

For every set of values for the decision variables and parameters, equation (14) is solved numerically for $r_{c,max}$. In practice, the value of r_c is much lower than the limit posed by equation (13). The value of $\tau_{3,max}$ is determined by the temperature which the materials can withstand. Theoretically, it is

$$r_{B,\max} = \eta_{\infty C,\max} = \eta_{\infty T,\max} = 1 \tag{15}$$

However, according to equation (5), η_{th} increases continuously with τ_3, $\eta_{\infty C}$, r_B, and $\eta_{\infty T}$. Therefore, the optimum values are set equal to the maximum values the current practice allows, although the theoretical limit of equation (15) cannot be achieved.

3.3 Maximization of the Net Power Density

A non-dimensional form of the net power density is used:

$$w \equiv \frac{\dot{W}}{\dot{m}_a c_{pa} T_1} \tag{16}$$

and the objective function is written as

$$\max\ w = (1+f)\frac{c_{pg}}{c_{pa}}\tau_3[1-(r_B r_C)^{-k_g \eta_{\infty T}}]-(r_C^{k_a/\eta_{\infty C}}-1) \qquad (17)$$

3.4 GA Results

Fig. 4 and Fig. 5 are results of optimization using genetic algorithms. Both of the optimization problems in sections 3.1 and 3.2 have been solved by Frangopoulos [7] for several values of τ_3, $\eta_{\infty C}$, $\eta_{\infty T}$ and the resulting optimum values of pressure ratio for maximum cycle efficiency $(r_c)_\eta$, and for maximum net power density, $(r_c)_w$, are presented in Fig. 4 and Fig. 5 respectively as marked points on the figures. The results obtained correspond well with the results obtained using GA. The results have been obtained with

$$H_u = 42500 \text{ kJ/kg}, \qquad T_1 = 298 \text{ K}, \qquad \tau_o = 1, \qquad r_B = 0.98$$

In addition to that, GA is also used to find additional data outside the range specified by the numerical results as shown in Fig. 4 and Fig 5. The numerical results show the data for non-dimensional temperature, τ_3 in the range of 4 to 5 while GA is used to find the additional results for τ_3 in the range of 3 to 6. The numerical results also show the data of the turbine polytropic efficiency, $\eta_{\infty T}$ from 0.82 to 0.90 while GA is used to find the same data for the range of 0.80 to 0.92. In the same way, GA is used to find additional values of the compressor polytropic efficiency, $\eta_{\infty C}$ in the range of 0.80 to 0.96 while the numerical results only show the values of $\eta_{\infty C}$ in the range of 0.84 to 0.92.

Results in Fig. 4 and Fig. 5 clearly demonstrate that GA is capable of producing results comparable to the numerical results.

4.0 THERMOECONOMIC DESIGN OPTIMIZATION

The same system studied in the first part will now be optimized with a thermoeconomic objective. Assumptions made in section 3.0 of the paper are applicable here too.

4.1 Objective Functions

Using the same relations as studied in [7], the objective functions will be optimized with GA and the results obtained with GA will be compared with the numerical results obtained by Frangopoulos.

The annual cost of owning and operating the system is selected as the objective function.

$$\min\ Z = Z_1 + Z_2 + Z_3 + c_f H_f \tag{18}$$

which consists of the annualized capital cost of equipment (including fixed charges and maintenance) and the cost of fuel. Other expenses (e.g. cost of lubricants, cost of electricity for the auxiliary equipment, etc.) are not included here, for simplicity.

The set of decision variables is the same as in the first part:

$$x = (r_C, r_B, \tau_3, \eta_{\infty C}, \eta_{\infty T}) \tag{19}$$

The annualized capital cost of compressor, combustor and turbine (the subcripts 1,2,3 are used instead of C,B,T respectively) is determined by equations obtained from El-Sayed and Tribus [9]:

$$Z_1 = \frac{c_{11}\dot{m}_a}{c_{12} - \eta_C} r_C \ln r_C \tag{20}$$

$$Z_2 = \frac{c_{21}\dot{m}_a}{c_{22} - r_B}[1 + \exp(c_{23}T_3 - c_{24})] \quad (21)$$

$$Z_3 = \frac{c_{31}\dot{m}_a}{c_{32} - \eta_T}\ln r_T[1 + \exp(c_{33}T_3 - c_{34})] \quad (22)$$

In order to determine the consumption, H_f, as well as dependent variables (e.g. $\dot{m}_a$, r_T) appearing in equations (20)-(22), an analysis of the system is performed, which gives the following equations:

$$T_2 = T_1 r_C^{k_a/\eta_{\infty C}} \quad (23)$$

$$T_3 = \tau_3 T_1 \quad (24)$$

$$r_T = r_B r_C \quad \text{(assumption: } P_4 = P_1\text{)} \quad (25)$$

$$T_4 = T_3 r_T^{-k_g/\eta_{\infty T}} \quad (26)$$

$$\dot{m}_a = \frac{\dot{W}}{\frac{H_u - c_{pa}(T_2 - T_0)}{H_u - c_{pa}(T_3 - T_0)} c_{pg}(T_3 - T_4) - c_{pa}(T_2 - T_1)} \quad (27)$$

$$\dot{m}_f = \frac{\dot{m}_a[c_{pg}(T_3 - T_0) - c_{pa}(T_2 - T_0)]}{H_u - c_{pg}(T_3 - T_0)} \quad (28)$$

$$H_f = \dot{m}_f H_u t \quad (29)$$

$$\eta_C = \frac{r_C^{k_a} - 1}{r_C^{k_a/\eta_{\infty C}} - 1} \quad (30)$$

$$\eta_T = \frac{1 - r_T^{-k_g \eta_{\infty T}}}{1 - r_T^{-k_g}} \quad (31)$$

The problem is optimized with the following constraints:

$$1 < r_C \le r_{C,\max} \tag{32}$$

$$\tau_2 < \tau_3 \le \tau_{3,\max} \tag{33}$$

$$0 < \eta_{\infty C} < 1 \tag{34}$$

$$0 < \eta_{\infty T} < 1 \tag{35}$$

$$0 < \eta_C < c_{12} \tag{36}$$

$$0 < r_B < c_{22} \tag{37}$$

$$0 < \eta_T < c_{32} \tag{38}$$

The upper limits c_{12}, c_{22}, c_{32} are imposed by the fact that values of Z_1, Z_2, and Z_3 must be nonnegative finite numbers. The parameters c_{12}, c_{22}, c_{32} and c_{r3} (r = 2,3) are related directly to one decision variable, $\eta_{\infty C}$, r_B, $\eta_{\infty T}$, and r_C respectively. Changes in these parameters with respect to changes in their related decision variables are given by Frangopoulos [7]. Equations (18), and (20)-(31) are then modeled in a C++ program and optimized with the specified constraints using GA. The nominal set of parameter values used is shown in Table 1. In addition to that, a sensitivity analysis is also carried out to find out how the optimum design would be affected by changes in parameter values.

Table 1. Nominal set of parameter values

$\dot{W} = 2.500$ kW	$c_{11} = 4.59$ (\$/yr)/(kg/s)	$c_{23} = 0.018$ K^{-1}	$C_{33} = 0.036$ K^{-1}
$T_0 = T_1 = 298$ K	$c_{12} = 0.90$	$c_{24} = 26.4$	$c_{34} = 54.4$
$H_u = 42500$ kJ/kg	$c_{21} = 3.09$ (\$/yr)/(kg/s)	$C_{31} = 31.0$ (\$/yr)/(kg/s)	
$c_f = 4 \times 10^{-6}$ \$/kJ	$c_{22} = 0.995$	$c_{32} = 0.92$	

4.2 Results

Table 2 shows a comparison of results for the optimum values of decision variables based on parameter values shown in Table 1. The steps involved are by fixing one of the decision variables (e.g. r_C) as the unknown variable and fixing the other four decision variable with their respective optimum values from Frangopoulos as shown in Table 2. That way the minimum cost function, equation (18) is then optimized for the first unknown decision variable, r_C. Using $r_B = 0.985$, $\tau_3 = 4.957$, $\eta_{\infty C} = 0.901$ and $\eta_{\infty T} = 0.860$, GA gives the value of r_C as 21.89. Similarly, using $r_C = 19.59$, $\tau_3 = 4.957$, $\eta_{\infty C} = 0.901$ and $\eta_{\infty T} = 0.860$, GA gives the values of $r_B = 0.986$. The values obtained this way are for fuel price $c_f = 4\times10^{-6}$ \$/kJ and are shown next to Frangopoulos' results in Table 2.

The results for the sensitivity analysis are shown in Figures 6-10. The figures show the comparison of results by superimposing results obtained using GA with the original results given by Frangopoulos [7]. The smooth continuous lines represent the GA results while the dotted lines represent Frangopoulos's results.

Table 2. Optimum values of the decision variables

Variable	Min Z (Frangopoulos)	Min Z (GA)
r_C	19.59	21.89
r_B	0.985	0.986
τ_3	4.957	4.843
$\eta_{\infty C}$	0.901	0.886
$\eta_{\infty T}$	0.860	0.882

5.0 DISCUSSION

Before GA is used as an optimizing tool, the problem above has to be modeled in C++ language and a program is written to represent the objective function of the problem together with all other governing equations. Once this is done, it is a matter of applying the program with GA to begin the optimization.

GA can work in many ways depending on how the objective function is defined in the program. In the first part of the gas turbine plant, the two objective functions are defined by equations (8) and (17) respectively. Having defined the objective functions, all other decision variables are fixed with their respective values with the exception of the compressor pressure ratio, r_C. Therefore, the objective function is dependent on the value of r_C alone. By optimizing the problem, the value of r_C that maximizes the objective function can be determined.

In the second part of the gas turbine plant, equation (18) is the objective function and equation (18) together with equations (20)-(31) are modeled in C++ and optimized with GA. The sensitivity analysis is also done with equation (18) as the objective function. Comparing the numerical results with the GA results in Figures 6-10, there are some differences in the results obtained. This is due to the reason that a lower limit for the total operation cost of the plant has not been given. The values produced by GA will give a minimum cost of zero, which is not a practical operating cost. Other than that, other uncertainties such as the operational time of the plant per year and the exact values for the principal parameters are also not provided. However the results obtained by GA are showing similar trends with the numerical results. Given the correct values of all the parameters used, it is possible for GA to obtain results comparable to the numerical results.

Not only is GA able to optimize a single variable function, GA is also capable of optimizing multi-variable function by giving the possible combination of values of the variables involved that maximizes the objective function. In the case of the gas turbine plant, with adequate constraints given, it is possible to let GA find a combination of the optimal values of $\eta_{\infty C}$, $\eta_{\infty T}$ and τ_3 that maximizes system efficiency. In the same way the optimum set of decision variables that minimizes cost can be obtained. GA can even generate the data for a given system with only the objective function and the governing equations alone. This is especially useful when there is a need to find additional data outside the range of the data obtained through experimental analysis or through numerical computation.

6.0 GA PARAMETERS

The optimization of the gas turbine plant with GA is done with the following GA parameters:

- Bit size: 30
- Population size: 100
- Number of generation: 10000
- Mutation rate: 0.044
- Crossover rate: 0.8867

7.0 CONCLUSIONS

Operating a gas turbine plant seems easy enough but ensuring that the operation is at an optimum level is rather complicated. There are too many factors to be considered and a wrong decision might increase the cost of operation. With so many decision variables that can be taken into consideration, typical optimization process by numerical method often requires lengthy computation. Furthermore, any change in the formulation requires a repetition of calculation.

It has been demonstrated that GA can be successfully implemented as an optimization tool for a simple gas turbine plant. The flexibility of GA enables it to perform various assessments for a given problem, and optimize the problem according to the formulation of the objective function. Other than used as an optimization tool, GA can also serve as a powerful search tool. With the increasing need for optimization in countless application of engineering systems, it is timely that GA be introduced as the preferred tool for search and optimization process.

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(: is the crossover point)

Chromosome 1	**11011:00100110110**
Chromosome 2	*11011:11000011110*
Offspring 1	**11011**:*11000011110*
Offspring 2	*11011*:**00100110110**

Figure 1. Crossover process

Original offspring 1	11011:1100***0***011110
Mutated offspring 1	11011:1100***1***011110
Original offspring 2	11011:00100110***1***10
Mutated offspring 2	11011:00100110***0***10

Figure 2. Mutation process

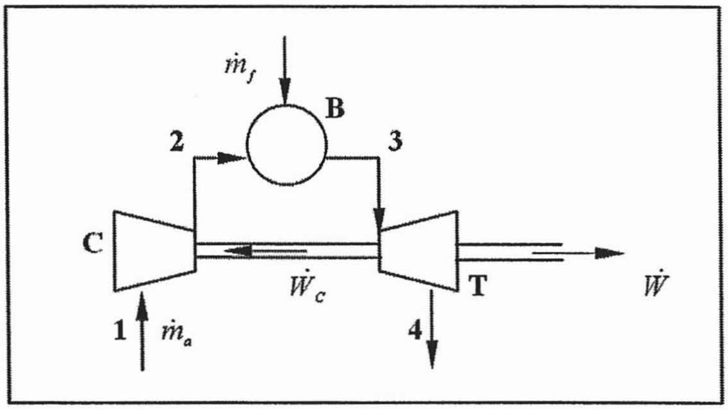

Figure 3. Simple Gas Turbine Plant

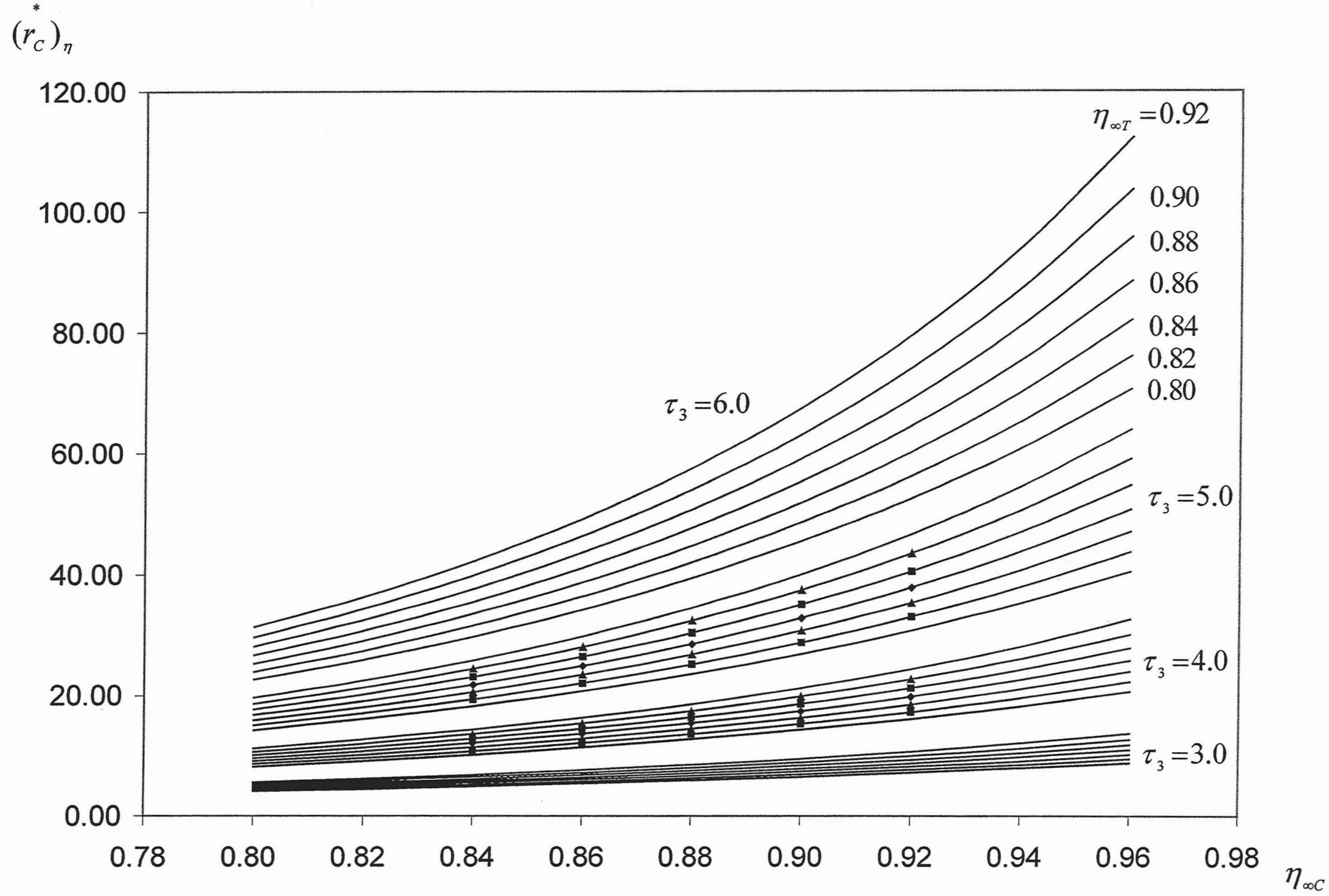

Figure 4. Effect of $\eta_{\infty C}$, $\eta_{\infty T}$ and τ_3 on the compressor pressure ratio for maximum efficiency.

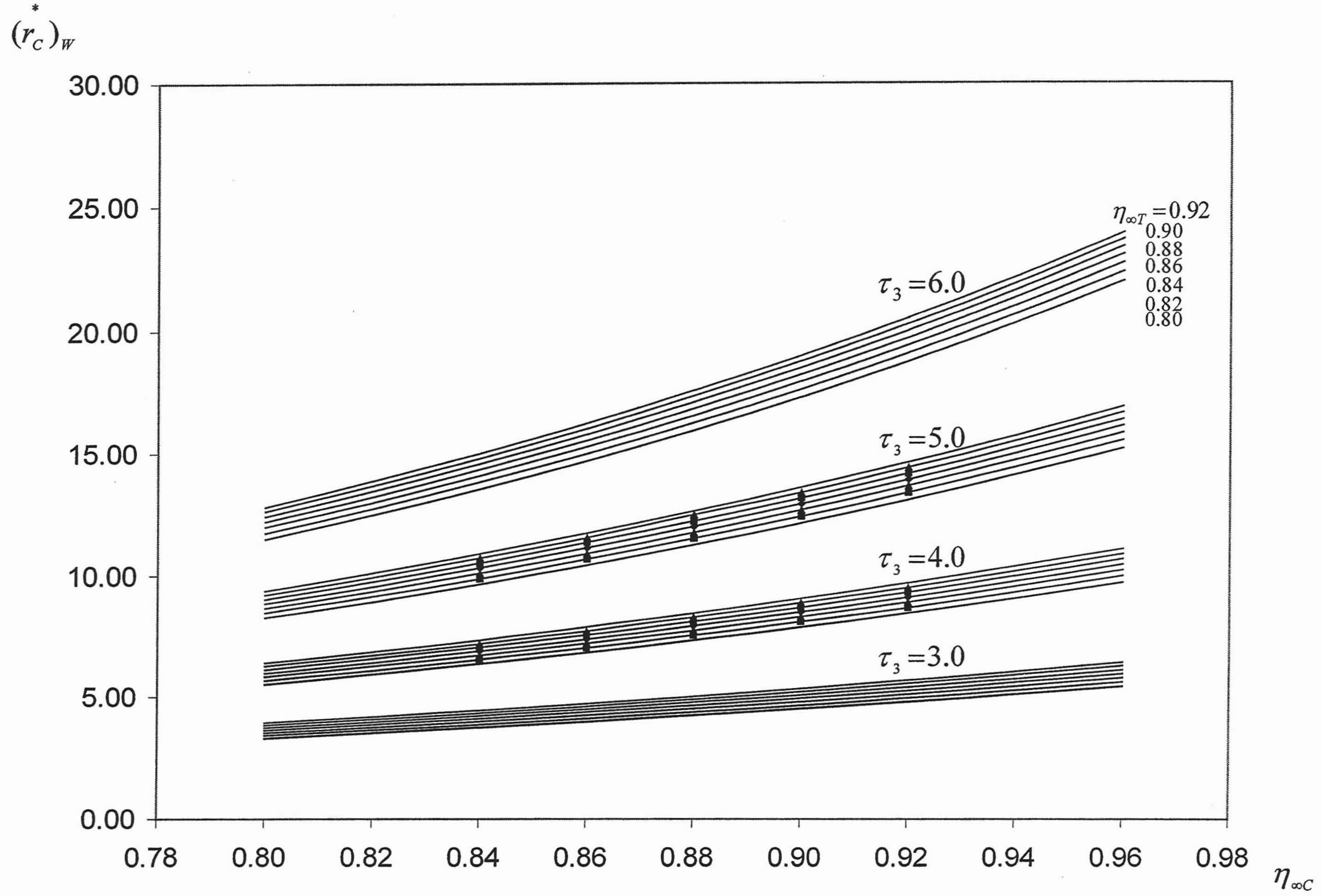

Figure 5. Effect of $\eta_{\infty C}$, $\eta_{\infty T}$ and τ_3 on the compressor pressure ratio for maximum net power density.

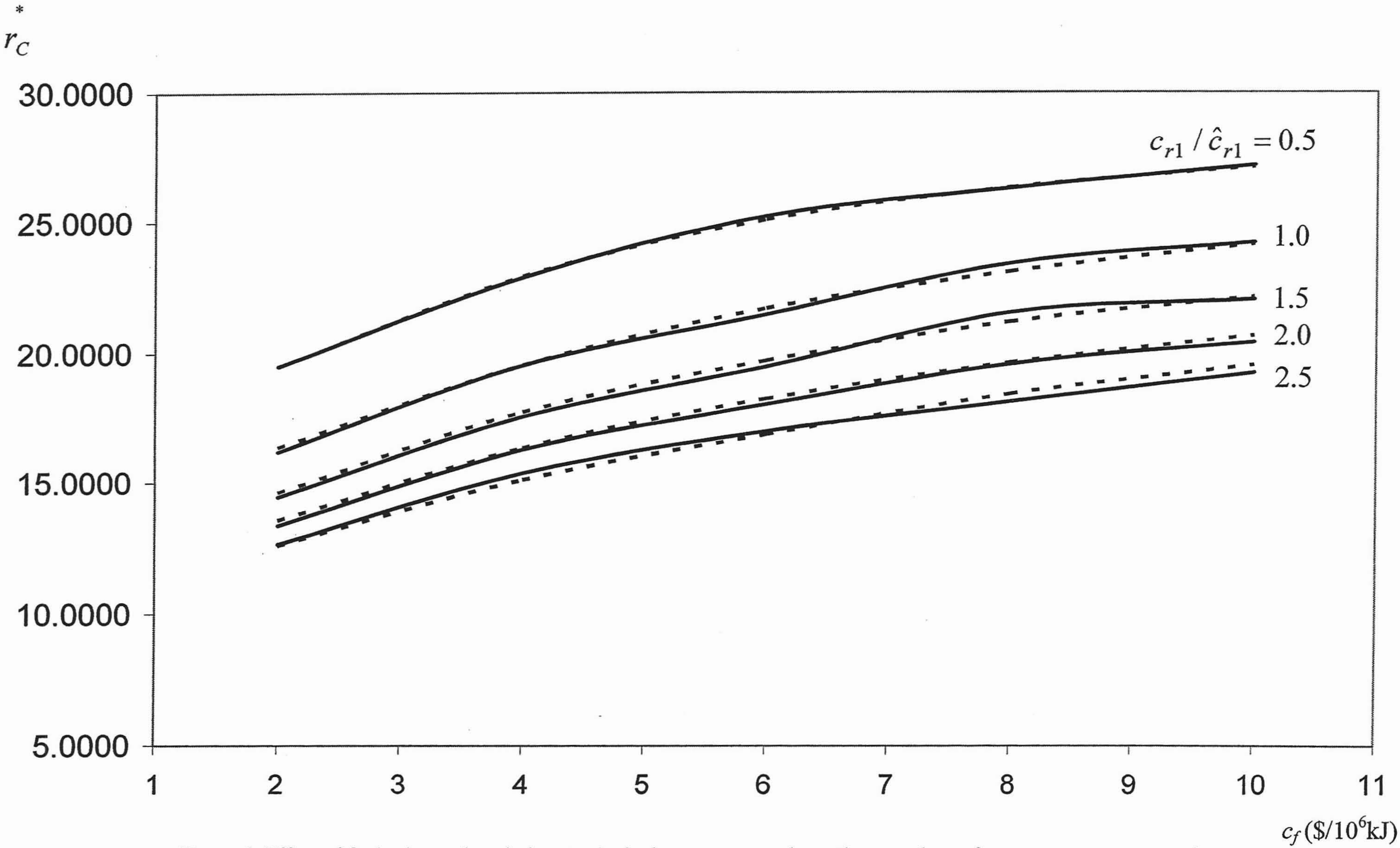

Figure 6. Effect of fuel price and capital cost principal parameter on the optimum values of compressor pressure ratio.

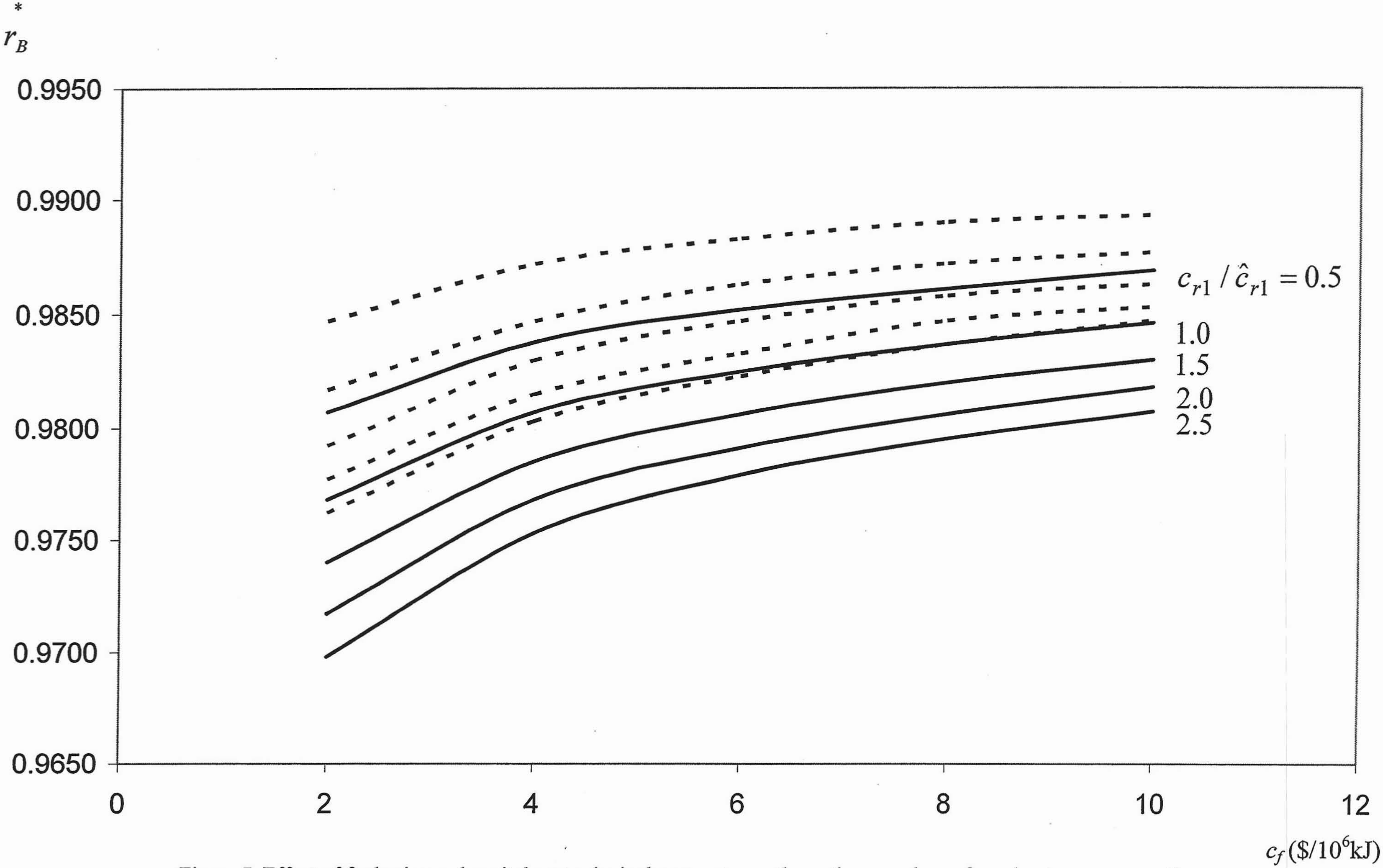

Figure 7. Effect of fuel price and capital cost principal parameter on the optimum values of combustor pressure ratio.

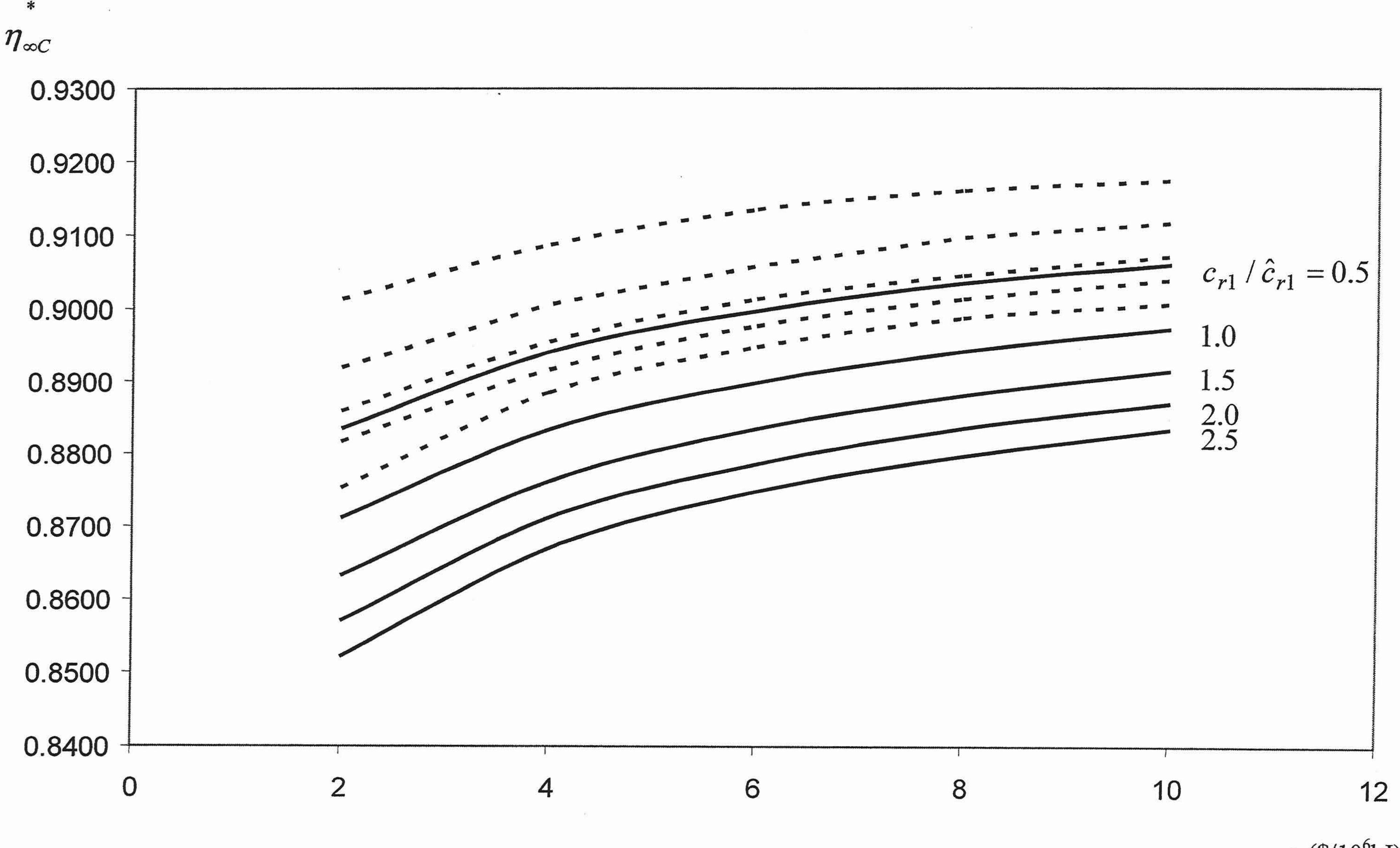

Figure 8. Effect of fuel price and capital cost principal parameter on the optimum values of polytropic efficiency of compressor.

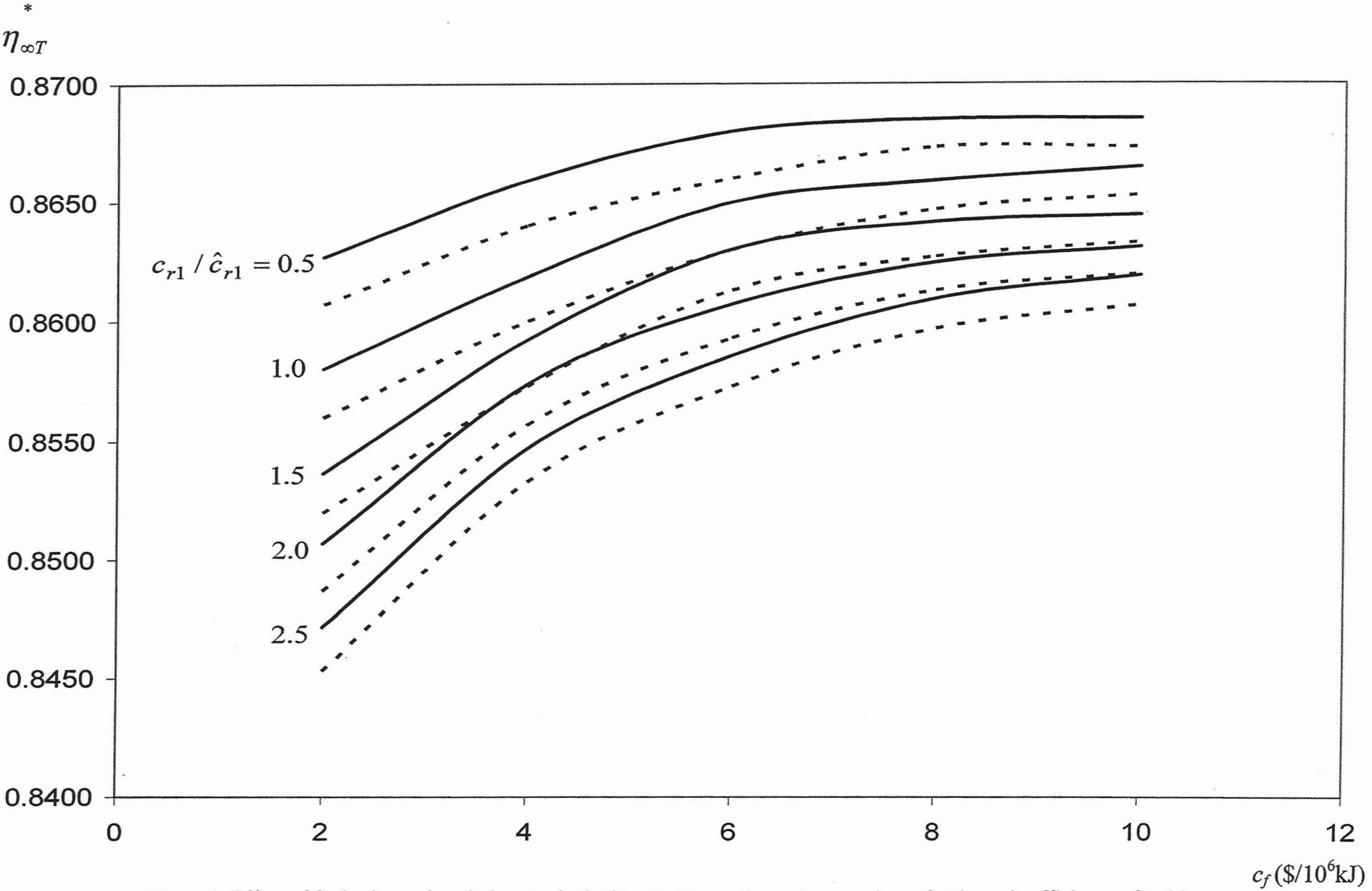

Figure 9. Effect of fuel price and capital cost principal parameter on the optimum values of polytropic efficiency of turbine.

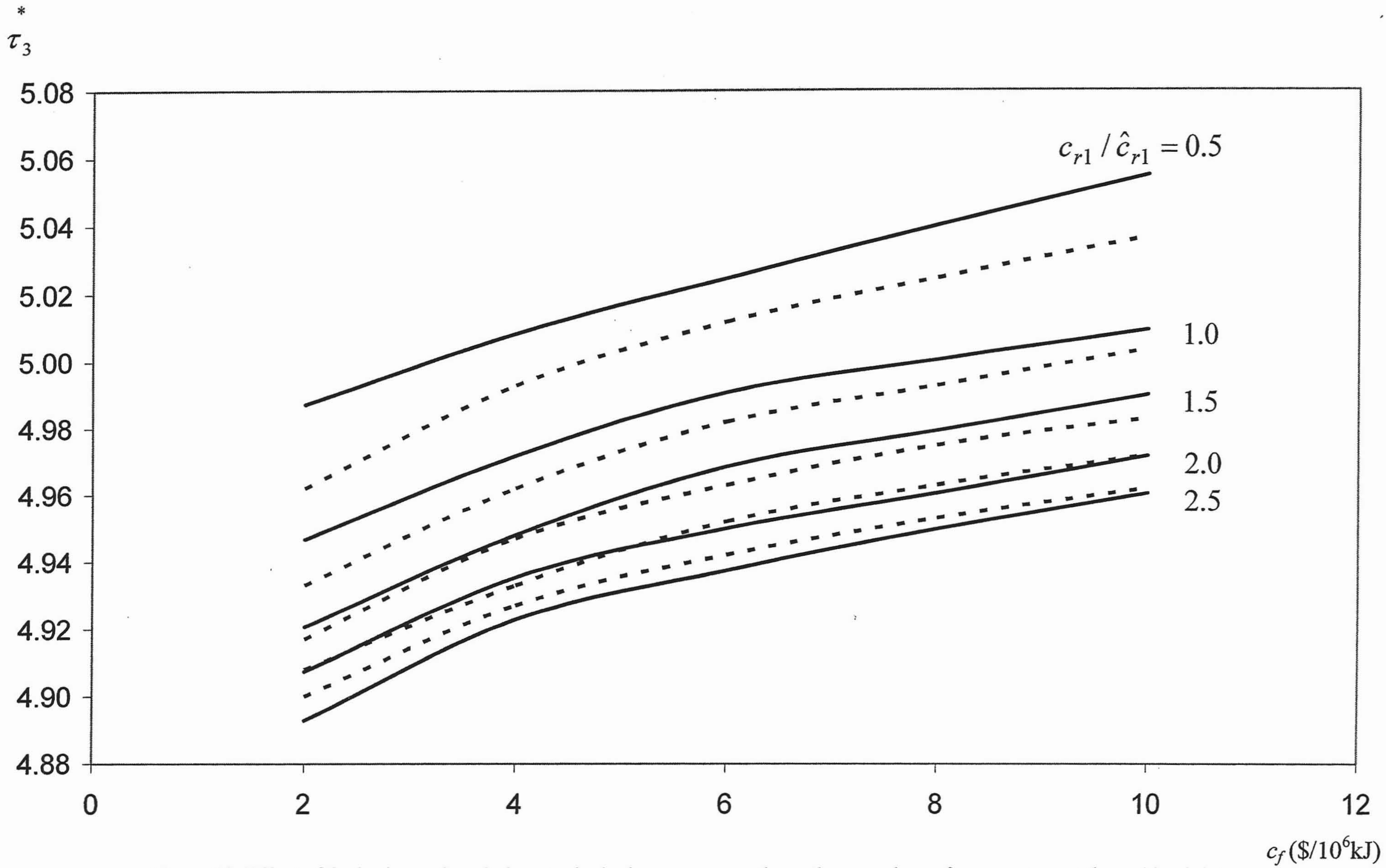

Figure 10. Effect of fuel price and capital cost principal parameter on the optimum values of temperature at the turbine inlet.