OPTIMIZATION OF GAS TURBINE CYCLE USING OPTIMIZATION TECHNIQUE

A
Thesis Report
submitted in partial fulfillment of the requirements for the award of degree

MASTER OF ENGINEERING
IN
CAD/CAM & ROBOTICS

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DECLARATION

I hereby declare that the work in this thesis report entitled "**OPTIMIZATION OF GAS TURBINE CYCLE BY OPTIMIZATION TECHNIQUE**" in partial fulfilment of requirement for the award of the master degree in CAD/CAM-Robotics submitted in the Mechanical Engineering Department, Thapar University, Patiala, is an authentic record of the initial work carried out by me under the guidance of **Mr. Sumeet Sharma, Assistant Professor, Mechanical Engineering Department, Thapar University, Patiala.**

The matter embodied in this report has not been submitted in part or full to any other university or institute for the award of any degree.

Date 15/JULY/2010.

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This is to certify that above declaration made by the student concerned is correct to the best of my knowledge & belief.

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PRINCE KUMAR

ABSTRACT

The present work is aimed to see the potentiality of optimization techniques in determination of cycle configuration of a gas turbine. The work is devoted to analyses and optimization of simple and sophisticated cycles of gas turbine engines to obtain the optimum design point in accordance with the demand of maximum thermal efficiency or maximum specific output. The optimization of criteria such as thermal efficiency and specific output can be formulated as a Neuro-Fuzzy Problem.

The solution of this Neuro-Fuzzy problem has been obtained with the help of Adaptive Neuro Fuzzy Inference System (ANFIS) in Matlab software. This technique is used for solving constrained optimization problems with objective and constraint function. The gas turbine system is divided into a number of sub-systems and operating state is expressed by design variables that govern such system.

The results obtained are quite satisfactory. ANFIS is quite accurate, efficient and fast. The results obtained are compared with those obtained by multiplier method to establish the validity of optimization procedure.

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DATA ASSUMED

θ = Maximum temperature ratio of cycle = 5

η_C = Compressor efficiency = 0.85

η_B = Burner efficiency = 0.98

η_T = Efficiency of turbine = 0.90

η_{HT} = Efficiency of high pressure turbine = 0.90

η_{LT} = Efficiency of low pressure turbine = 0.88

η_{EX} = Efficiency of heat- exchanger = 0.75

η_{IC} = Efficiency of intercooler = 0.85

ε_b = Pressure loss co-efficient of burner = 0.03

ε_{EX} = Pressure loss co-efficient of heat-exchanger = 0.03

ε_{IC} = Pressure loss co-efficient of intercooler = 0.03

C_P = Specific heat = 1.114 KJ/Kg K

T_{in} = Ambient temperature = 288.15 K

T_W = Temperature of water = 288.15 K

LIST OF SYMBOLS

B = Combustion chamber

C = Compressor

C_P = Specific heat (KJ/kg K)

HT = High pressure turbine

IC = Intercooler

l = Specific output (KW/Kg sec)

I = Non-dimensional specific output

LT = Low pressure turbine

P_{out} = Pressure at inlet of the combustion chamber

P_{bexit} = Pressure at outlet of the combustion chamber

T_{max} = Maximum temperature of the cycle

T_{in} = Temperature at inlet to the compressor

T_{out} = Temperature at outlet to the compressor

T_{out1} = Temperature at outlet of the first compression

T_{out2} = Temperature at outlet of the second compression

T_E = Temperature at outlet of the turbine

T_{EX} = Temperature at outlet of the regenerator

T_e = Temperature at outlet of the low pressure turbine

T_{E1} = Temperature at outlet of the high pressure turbine

T_W = Temperature of the water

Z = Total performance function

α = Weighing parameter

θ = Cycle maximum temperature ratio

θ_C = Temperature ratio of the compressor

θ_{C1} = Temperature ratio of the low pressure compressor

θ_{C2} = Temperature ratio of the high pressure compressor

θ_E = Temperature ratio of the regenerator

θ_{HT} = Temperature ratio of the high pressure turbine

θ_{LT} = Temperature ratio of the low pressure turbine

θ_T = Temperature ratio of the

CHAPTER 1 INTRODUCTION

1.1 PREFACE

Power generation is an important issue today. Demand is outweighing supply because of lack of incentives for the utilities industry to build additional power plants over the past 10-20 years. Electrical innovations (such as the personal computer) were not accounted for in earlier predictions of power utilization and, now, the country is in dire need of streamlining the current power plants while pushing through as many applications as possible for new power plants. In response to this situation, power generation engineers will be in high demand. These engineers must have a thorough understanding of thermodynamics and, in particular, the Brayton cycle. It is the backbone of power generation.

The two major application areas of gas-turbine engines are aircraft propulsion and electric power generation. Gas turbines are used as stationary power plants to generate electricity as stand-alone units or in conjunction with steam power plants on the high-temperature side. This process is called cogeneration. In these plants, the exhaust gases serve as a heat source for the steam. Steam power plants are considered external-combustion engines, in which the combustion takes place outside the engine. The thermal energy released during this process is then transferred to the steam as heat.

As the area of application of gas turbine is extended, the thermodynamic cycle of gas turbine becomes more sophisticated. The gas turbine basically consists of compressor, combustor and a turbine. By the inclusion of heat exchangers such as regenerator the amount of fuel required can be reduced which increases the thermal efficiency. The increase in the number of components, however, requires more elaborate analysis to determine the conditions for the cycle. In the present study, the cycle is divided into a number of sub-system or components. The operating state is expressed by parameters that govern such sub-systems. The criteria of optimization are thermal efficiency and specific work done. The optimization of above mentioned criteria is solved with the help of Adaptive Neuro Fuzzy Inference System. This method can be employed for simple and sophisticated cycles as well as for giving the optimum values of parameters in short time. This is an artificial intelligent method which can further predict the values of optimum parameters for different configurations. This is one of the latest technique is developed recently.

1.2 HISTORY OF GAS TURBINES

The gas turbine has experienced phenomenal progress and growth since its first successful development in the 1930’s. The early gas turbines built in the 1940’s and even 1950’s had simple-cycle efficiencies of about 17 percent because of the low compressor and turbine efficiencies and low turbine inlet temperatures due to metallurgical limitations of those times. Therefore, gas turbines found only limited use despite their versatility and their ability to burn a variety of fuels. The efforts to improve the cycle efficiency concentrated in three areas:

1. Increasing the turbine inlet (or firing) temperatures.

2. Increasing the efficiencies of turbo-machinery components.

3. Add modifications to the basic cycle.

The simple-cycle efficiencies of early gas turbines were practically doubled by incorporating intercooling, regeneration (or recuperation), and reheating. The back work ratio of a gas-turbine cycle improves as a result of intercooling and reheating. However, this does not mean that the thermal efficiency will also improve. Intercooling and reheating will always decrease the thermal efficiency unless they are accompanied by regeneration. This is because intercooling decreases the average temperature at which heat is added, and reheating increases the average temperature at which heat is rejected. Therefore, in gas-turbine power plants, intercooling and reheating are always used in conjunction with regeneration. These improvements, of course, come at the expense of increased initial and operation costs, and they cannot be justified unless the decrease in fuel costs offsets the increase in other costs. In the past, the relatively low fuel prices, the general desire in the industry to minimize installation costs, and the tremendous increase in the simple-cycle efficiency due to the first increased efficiency options to approximately 40 percent left little desire for incorporating these modifications. With continued expected rise in demand and cost of producing electricity, these options will play an important role in the future of gas- turbine power plants. The purpose of this paper is to explore this third option of increasing cycle efficiency via intercooling, regeneration, and reheating. By including various heat exchangers like intercooler, regenerator and reheater in the gas turbine cycle the thermal efficiency and the specific work done can be increased and enhancing the performance of the gas turbine.

1.3 REFINEMENTS IN GAS TURBINE CYCLE

Gas turbines installed until the mid-1970's suffered from low efficiency and poor reliability. In the past, large coal and nuclear power plants dominated the base-load electric power generation. Base load units are on line at full capacity or near full capacity almost all of the time. They are not easily nor quickly adjusted for varying large amounts of load because of their characteristics of operation. However, there has been a historic shift toward natural gas-fired turbines because of their higher efficiencies, lower capital costs, shorter installation times, better emission characteristics, the abundance of natural gas supplies, and shorter start up times. Now electric utilities are using gas turbines for base-load power production as well as for peaking, making capacity at maximum load periods and in emergency situations because they are easily brought on line or off line. The construction costs for gas-turbine power plants are roughly half that of comparable conventional fossil fuel steam power plants, which were the primary base-load power plants until the early 1980's, but peaking units are much higher in energy output costs.

Gas turbines usually operate on an open cycle. Fresh air at ambient conditions is drawn into the compressor, where its temperature and pressure are raised. The high-pressure air proceeds into the combustion chamber, where the fuel is burned at constant pressure. The resulting high-temperature gases then enter the turbine, where they expand to the atmospheric pressure through a row of nozzle vanes. This expansion causes the turbine blade to spin, which then turns a shaft inside a magnetic coil. When the shaft is rotating inside the magnetic coil, electrical current is produced. The exhaust gases leaving the turbine in the open cycle are not re-circulated.

The open gas-turbine cycle can be modelled as a closed cycle by utilizing the air-standard assumptions. Here the compression and expansion process remain the same, but a constant-pressure heat-rejection process to the ambient air replaces the combustion process. The ideal cycle that the working fluid undergoes in this closed loop is the Brayton cycle, which is made up of four internally reversible processes. Using a closed cycle for the gas turbine develops the possibility of using a high pressure (and hence a high gas density) throughout the cycle, which would result in a reduced size of turbo-machinery for a given output. The schematic diagram of the open cycle gas turbine is shown in Fig. 3.6.

The closed cycle open up the possibilities of the use of gases other than air having more desirable thermal properties. The monatomic gas such as helium which has the high value of specific heat can be used as working fluid. The better heat transfer characteristics of helium means that the size of the heat-exchanger and pre-cooler can be about half that of units designed for use with air.

1.4 ORGANIZATION OF THESIS

The thesis work is formulated into seven chapters. First chapter is introductory in nature. Second chapter deals with the literature review and the research studies which had been made in this field. Third chapter includes gas turbine cycles, their configurations and various gas turbine components. Chapter four deals with the derivation of expression for efficiency and non-dimensional specific output of all four configurations. Chapter five is included to discuss the various techniques used for optimization. It also explains the technique which is used in this present work i.e. Adaptive Neuro Fuzzy Inference System (ANFIS) in detail. Sixth chapter deals with problem formulation for different configurations which includes objective function, design variables and constraints for all configurations. The last chapter i.e. seventh includes the results and discussions in which optimum numerical results obtained for each of the configurations. The results obtained are compared with those of the Multiplier Method. The appendix gives the computer program and the training data for the different configurations.

CHAPTER 2 LITERATURE REVIEW

In order to have an idea of present technological development in the area of gas turbine, its performance and optimization, a brief survey of available literature is made. A number of research studies, both experimental and numerical, on the optimization of gas turbine cycle and neural networks.

2.1 REVIEW OF LITRETURE

Andreas Poullikkas et al. [1] in his work gave an overview of current and future sustainable gas turbine technologies. In his research work, the various gas turbine technologies are described and compared. Emphasis had been given to the various advance cycles involving heat recovery from the gas turbine exhaust, such as, the gas to gas recuperation cycle and the combined cycle The thermodynamic characteristics of the various cycles are considered in order to establish their relative importance to future power generation markets. The combined cycle technology is now well established and offers superior to any of the competing gas turbine based systems, which are likely to be available in the medium term for large-scale power generation applications. In small-scale generation, less than 50 MW it is more cost effective to install a less complex power plant from economic point of view. Combined cycle plants in this power output range normally have higher specific investment costs and lower electrical efficiencies but also offer robust and reliable performance

Yousef S.H. Najjar et al. [2] described that the efficiency of the gas turbine engine is relatively low at design point and it deteriorates further at part load and at off-design high ambient temperatures. His work comprises the study of adding an inlet air precooler driven by the tail-end heat recovered from the engine exhaust gases. A heat recovery boiler is used to partly recover the exhaust heat. The performance of this combined system, namely power, efficiency and specific fuel consumption is studied and compared with the simple cycle. The variables in this parametric study are mainly compressor pressure ratio, turbine inlet temperature and ambient temperature. Results show that the combined system achieves gains in power. The performance of the combined system showed less sensitivity to variations in operating variables. Thermo economic evaluation shows that the combined system is viable.

Lingen Chen et al. [3] studied performance analysis and optimization of an open-cycle regenerator gas-turbine power plant. The analytical formulae about the relation between power output and cycle overall pressure-ratio are derived taking into account the eight pressure-drop losses in the intake, compression, regeneration, combustion, expansion and discharge processes and flow process in the piping, the heat-transfer loss to the ambient environment, the irreversible compression and expansion losses in the compressor and the turbine, and the irreversible combustion loss in the combustion chamber. The power output was optimized by adjusting the mass-flow rate and the distribution of pressure losses along the flow path. Also, it was shown that the power output has a maximum with respect to the fuel-flow rate or any of the overall pressure-drops and the maximized power output had an additional maximum with respect to the overall pressure-ratio. The numerical example showed the effects of design parameters on the power output and heat-conversion efficiency.

Anita Kovac Kralj et al. [4] investigated that heat and power integration can reduce fuel usage, carbon dioxide and sulphur dioxide emissions and, thereby, pollution. In the simultaneous heat and power integration approach and including additional production, the optimization problem is formulated using a simplified process superstructure. Nonlinear programming (NLP) contains equations which enable structural heat and power integration and parametric optimization. In this study the NLP model is formulated as an optimum energy target of process integration and electricity generation using a gas turbine with a separator. The reactor acts as a combustion chamber of the gas turbine plant, producing high temperature. The simultaneous NLP approach can account for capital cost, integration of combined heat and power, process modification, and additional production trade-offs accurately, and can thus yield a better solution. It gives better results than other methods. The NLP model does not guarantee a global cost optimum, but it does lead to good, perhaps near optimum designs.

Xiaoyong Qin et al. [5] developed the genetic optimization theory; a design method for the flow path of an axial flow steam turbine stage. In this method the maximum efficiency of the stage is taken as the objective, a series of functions are taken as constraints, and the optimal geometric and aerodynamic parameters are solved using the genetic algorithm process. The efficiency and constraints evaluation are performed using a program for the thermodynamic calculation of steam turbine stages in the design condition. The fitness of each individual is determined by the turbine efficiency and a penalty function containing the constraints. The proposed method is applied to the design of a real steam turbine stage. The results showed that the new method successfully reveals the optimal geometric and aerodynamic parameters of the stage for maximum efficiency.

Valceres V.R. Silva et al. [6] states that performance optimization of a gas turbine engine can be expressed in terms of minimizing fuel consumption while maintaining nominal thrust output, maximizing thrust for the same fuel consumption and minimizing turbine blade temperature. Additional control layers are used to improve engine performance. This paper presents an evolutionary approach called the StudGA as the optimization framework to design for optimal performance in terms of the three criteria above. This approach converges fast and can potentially save on computing cost. Model-based experimental results are used to illustrate this approach.

Y. Tsujikawa et al. [7] devoted his study to the analyses and optimization of simple and sophisticated cycles, particularly for various gas turbines engines and aero-engines (including scramjet engine) to achieve maximum performance. The optimization of such criteria as thermal efficiency, specific output and total performance for gas turbine engines and overall efficiency, non-dimensional thrust, specific impulse for aero-engines has been performed by optimization procedure with the multiplier method. Comparison of results with analytical solutions establishes the validity of the optimization procedure.

Manuel Valdes et al. [8] this paper showed a possible way to achieve a thermoeconomic optimization of combined cycle gas turbine (CCGT) power plants. The optimization has been done using a genetic algorithm, which has been tuned applying it to a single pressure CCGT power plant. Once tuned, the optimization algorithm has been used to evaluate more complex plants, with two and three pressure levels in the heat recovery steam generator (HRSG). The variables considered for the optimization were the thermodynamic parameters that establish the configuration of the HRSG. Two different objective functions were proposed: one minimizes the cost of production per unit of output and the other maximizes the annual cash flow. The results obtained with both functions are compared in order to find the better optimization strategy. The results show that it is possible to find an optimum for every design parameter. This optimum depends on the selected optimization strategy.

Mallinson et al. [9] investigated the part load performance of various gas turbine engine schemes and conventional three group notation given by them has been adopted here also.

Bernardo Morcego Seix et al. [10] explained the ways in which neural networks are suitable models for qualitative techniques to be applied. It explored how qualitative reasoning could deal with the well known back-propagation learning algorithm. Qualitative models are based on the discretization of their parameters and the use of closed operators on the sets induced by the discretization. Henceforth, a qualitative version of back-propagation is an algorithm in which the variables involved in it belong to one among the finite classes defined. It can be very useful either to realize a physical implementation of the algorithm or as a starting point to develop new reinforcement learning algorithms for neural networks.

O. Cortés et al. [11] had developed a way to optimize the parameters (i.e. operating conditions), related to compressor performance, and based on artificial neural network. It inverts the neural network to find the optimum parameter value under given conditions (artificial neural network inverse, ANNi). In order to do so, first an artificial neural network (ANN) was developed to predict: compressor pressure ratio, isentropic compressor efficiency, corrected speed, and finally corrected air mass flow rate. Input variables for this ANN include: ambient pressure, ambient temperature, wet bulb temperature, cooler temperature drop, filter pressure drop, outlet compressor temperature, outlet compressor pressure, gas turbine net power, exhaust gas temperature, and finally fuel flow mass rate. For the network, a feed-forward with one hidden layer algorithm, a hyperbolic tangent sigmoid transfer-function and a linear transfer-function were used. The best fitting with the training database was obtained with 12 neurons in the hidden layer. For the validation of present database, simulation and experimental database were in good agreement. Thus, the obtained ANN model can be used to predict the operating conditions when input parameters are well-known. Second, results from the ANNi that was developed also show good agreement with experimental and target data (error <0.1%), in this case, cooler temperature was found for a required efficiency. Therefore, the proposed methodology of ANNi can be applied to optimize the performance of the compressor with an elapsed time minor to 0.5 s.

Jyh Shing Roger Jang [12] explained the architecture and learning procedure of ANFIS (Adaptive Neuro Fuzzy Inference System), which is a fuzzy inference system implemented in the framework of adaptive networks. By using a hybrid learning procedure, the proposed ANFIS can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs. In the simulation, the ANFIS architecture is employed to model nonlinear functions, identify nonlinear components and predict a chaotic time series, all yielding remarkable results. Other extensions of the proposed ANFIS and promising applications to automatic control and signal processing are also suggested in his research work.

A. Abraham et al. [13] explained that the integration of neural networks and fuzzy inference systems can be formulated into three main categories: cooperative, concurrent and integrated neuro-fuzzy models. He presented three different types of cooperative neuro fuzzy models namely fuzzy associative memories, fuzzy rule extraction using self-organizing maps and systems capable of learning fuzzy set parameters. Different Mamdani and Takagi-Sugeno type integrated neuro-fuzzy systems are further introduced with a focus on some of the salient features and advantages of the different types of integrated neuro-fuzzy models that had been evolved during the last decade

Alaa Sheta et al. [14] had discussed that there are variety of problems in mechanical, electrical, chemical and aerospace engineering that can be formulated as Non-Linear Programming (NLPs). The quality of the developed solution significantly affects the performance of such systems. In this paper the ability of Genetic Algorithms (GAs) to tackle the constrained NLPs problems is investigated. The experimental results which are obtained in this work indicate that GAs can effectively solve these types of problems. GAs can overcome many problems encountered by traditional search techniques as gradient based methods. The performance of GAs is compared to the Sequential Quadratic Programming (SQP) method.

W. Ruijter et al. [15] presented in his research wrk the first results of a running study on optimization of aircraft components (composite panels of a typical vertical tail plane) by using Genetic Algorithms (GA) and Neural Networks (NN). The panels considered were standardized to some extent but still there was a wide scope of discrete and continuous design variables that can be adjusted to increase performance or reduce structural weight. A NN was trained for every panel configuration using a back-propagation algorithm with data sets taken from finite element analyses spread randomly over the design space. The trained network is then used to predict the values of the constraint functions (strain and buckling multipliers). The approach was formulated in this manner to maintain maximum flexibility regarding the implementation of new variables or models and with the prospect of optimizing the assembly as a whole. Results showed that in design problems with high dimensionality the approach becomes more attractive, especially when the optimization has to be run repeatedly for panels under different loading/sizing conditions. The optimization algorithm had proven to be robust though dependent on the smoothness of the network output function. A modified method that feeds back the found optima was proposed to improve accuracy of the NN and decrease preparation time.

Krzysztof Kosowski et al. [16] in his study proposed a general, efficient system for designing turbine cascades and stages in real 3D-flow conditions. The presented algorithms involve application of evolutionary algorithms, as well as Artificial Neural Networks. Results of the design process were shown to be highly optimized in terms of efficiency, whereas computation time is reduced by several orders of magnitude in comparison to methods relying on Computational Fluid Dynamics calculations.

Jiangfeng Wang et al. [17] explained that in the supercritical CO2 power cycle there is a high potential to recover low-grade waste heat due to its better temperature glide matching between heat source and working fluid in the heat recovery vapor generator (HRVG). Parametric analysis and energy analysis were conducted to examine the effects of thermodynamic parameters on the cycle performance and energy destruction in each component. The thermodynamic parameters of the supercritical CO2 power cycle was optimized with energy efficiency as an objective function by means of genetic algorithm (GA) under the given waste heat condition. An artificial neural network (ANN) with the multi-layer feed-forward network type and back-propagation training is used to achieve parametric optimization design rapidly. It showed that the key thermodynamic parameters, such as turbine inlet pressure, turbine inlet temperature and environment temperature had significant effects on the performance of the supercritical CO2 power cycle and energy destruction in each component. It is also shown that the optimum thermodynamic parameters of supercritical CO2 power cycle can be predicted with good accuracy using artificial neural network under variable waste heat conditions.

The literature survey for the cycles and configuration and the study of various possible gas turbine configurations, detailed account of various aspects of axial flow turbines such as basic principles, combustion process, work output and factors upon which it depends has been given by **H. Cohen and G. F. C. Rogers [18].**

The evaluation and method of accounting component losses and information about the temperature-entropy diagram have been given by **D.S. Kumar, V. P. Vasandani [19]** and **J. H. Horlock [20]**.

Shepherd [21] is considered as an authority on the principles of turbo machinery. The description of topics undertaken is immensely helpful in understanding the basic principles involved in the operation of a turbo machine.

2.2 OBJECTIVE OF PRESENT WORK

It has been observed that the potentiality of the gas turbine optimization has not been done to much extent. This thesis work is devoted to analyses and optimization of gas turbine cycle for different configurations. The objective is to optimize the thermal efficiency and specific work done. The various configurations that will discuss are 1/C – having a compressor turbine and combustor, 1/C/E – having a compressor, regenerator, combustor and turbine, in 1/LP scheme the high pressure turbine drives the compressor and low pressure turbine gives the network output and in 1/LP/E a heat exchanger is added to the 1/LP configuration to recover heat from the exhaust of low pressure turbine, to decrease the amount of fuel required which increases the thermal efficiency. The method used for optimization in this work is Adaptive Neuro Fuzzy Inference System (ANFIS) which uses Takagi-Sugeno Integrated Neuro-Fuzzy System which is a Artificial Intelligent technique. In the present, gas turbine is regarded as a system consisting of number of sub-systems. The various design variables used are temperature ratios and various components and are assigned certain initial values and then optimized. Constraints, design variables and objective function for each configuration are different and are described accordingly in subsequent chapters.

Gas turbine engines are, theoretically, extremely simple. They have three parts:

- **COMPRESSOR -** Compresses the incoming air to high pressure.
- **COMBUSTION AREA -** Burns the fuel and produces high-pressure, high-velocity gas.
- **TURBINE -** Extracts the energy from the high-pressure, high-velocity gas flowing from the combustion chamber.

The following figure shows the general layout of an axial-flow gas turbine

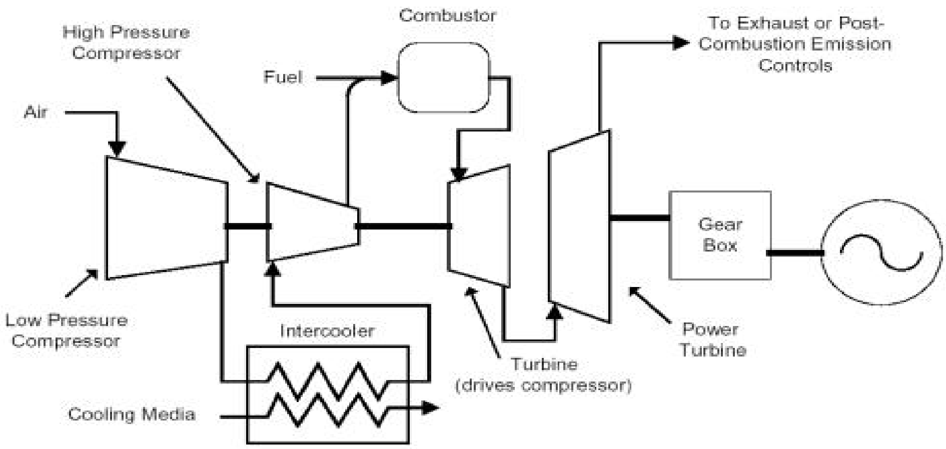

FIG 3.1: GAS TURBINE SYSTEM

As shown in Fig. 3.1, air is sucked in from the compressor. The compressor is basically an axial flow compressor with blades attached in rows. As the air is forced through each of the compression stage its pressure rises significantly. In some engines, the pressure of the air can rise by a factor of 30.

3.1 THEORY OF GAS TURBINE COMPONENTS

3.1.1 COMPRESSOR

Efficient compression of large volumes of air is essential for a successful gas turbine engine. This has been achieved in two types of compressors, the axial-flow compressor and the centrifugal compressor. Most power plant compressors are axial-flow compressors because they are able to handle large mass flow rates. The objective of a good compressor design is to obtain the most air through a given diameter compressor with a minimum number of stages while retaining relatively high efficiencies and aerodynamic stability over the operating range. Compressors contain a row of rotating blades followed by a row of stationary (stator) blades. A stage consists of a row of rotor and a row of stator blades. All work done on the working fluid is done by the rotating rows, the stators converting the fluid kinetic energy to pressure and directing the fluid into the next rotor. The fluid enters with an initial velocity relative to the blade and leaves with a final relative velocity at a different angle.

3.1.1.1 CENTRIFUGAL AIR COMPRESSOR

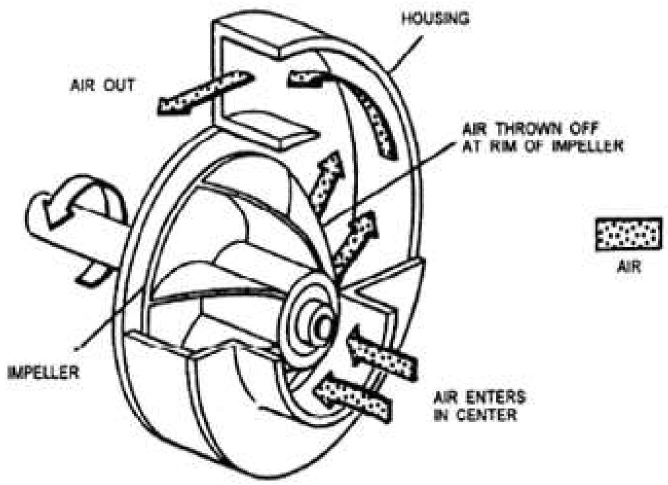

FIG 3.2: CENTRIFUGAL COMPRESSOR

The impeller, which consists of large number of blades, is mounted on the compressor shaft, inside the stationary casing. As the impeller rotates, the pressure in suction region falls and hence the air enters through the eye and flows radically outwards through impeller blades. As a result velocity and pressure of air increases. Later this air enters and flows through the divergent passages formed by the diffuser blades. At this stage the velocity of air is decreases but the pressure increases still further. We may say that, during this stage the kinetic energy is converted into pressure energy. Finally this high pressure air escapes from the compressor delivery portion. By this method we can obtain high pressure ratios by arranging the number of air compressor in series. The schematic diagram of the centrifugal compressor is shown in the Fig. 3.2.

3.1.1.2 AXIAL AIR COMPRESSOR

These types of compressors are more commonly used now a day. In axial compressor, the air flows in an axial direction right from intake to the discharge. The stator, which has stator blades, encloses the rotor, which is provided with rotor blades. As the air enters from suction region, it flows through the alternately arranged stator and rotor blade rings. In flowing through each pair of blade rings formed up of one rotor blade ring and one stator blade ring, the air gets compressed successively. The air is finally delivered from delivery region, which is smaller in size compare to suction side.

Axial flow compressors produce a continuous flow of compressed gas, and have the benefits of high efficiencies and large mass flow capacity, particularly in relation to their cross-section. They do, however, require several rows of airfoils to achieve large pressure rises making them complex and expensive relative to other designs.

The Fig. 3.3 shows a cross section of an axial compressor with multiple impellers. The gas flows axially along the shaft of the compressor from one impeller to another, directed by the stationary vanes. Each impeller/stationary vane set represents one stage of compression. The fluid is accelerated by impeller vanes and subsequently it is decelerated in the stator vanes which then guide it into next stage of impeller vanes.

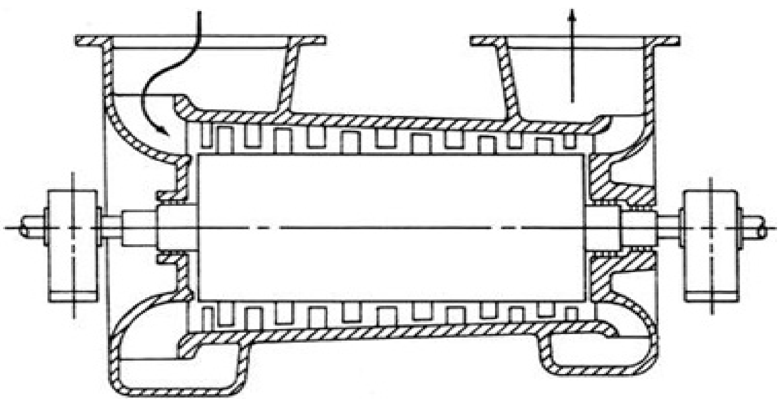

FIG 3.3: AXIAL FLOW COMPRESSOR

Axial compressors are widely used in gas turbines, such as jet engines, high speed ship engines, and small scale power stations. They are also used in industrial applications such as large volume air separation plants, blast furnace air, fluid catalytic cracking air, and propane dehydrogenation. Axial compressors, known as superchargers, have also been used to boost the power of automotive reciprocating engines by compressing the intake air, though these are very rare.

3.1.2 COMBUSTION CHAMBER (COMBUSTOR)

Combustion is the chemical combination of a substance with certain elements, usually oxygen, accompanied by the production of a high temperature or transfer of heat. The function of the combustion chamber is to accept the air from the compressor and to deliver it to the turbine at the required temperature, ideally with no loss of pressure. Essentially, it is a direct-fired air heater in which fuel is burned with less than one-third of the air after which the combustion products are then mixed with the remaining air. For the common open-cycle gas turbine, this requires the internal combustion of fuel. This means the problem of fuel operation, mixing and burning, must be addressed. Fuel is commonly gaseous or liquid. Gaseous or liquid fuels are usually hydrocarbons. Gases usually being natural gas, mostly methane, and butane. Liquids may range from highly refined gasoline through kerosene and light diesel oil to a heavy residual oil. Combustion itself possesses great difficulties. The difficulty arises because of pressure loss in combustion chamber. Almost any fuel can be burnt successfully if sufficient pressure drop is available to provide the necessary turbulence for mixing of air and fuel and if sufficient volume is available to give the necessary time for combustion to be completed.

This high-pressure air then enters the combustion area, where a ring of fuel injectors injects a steady stream of fuel. The fuel is generally kerosene, jet fuel, propane or natural gas.

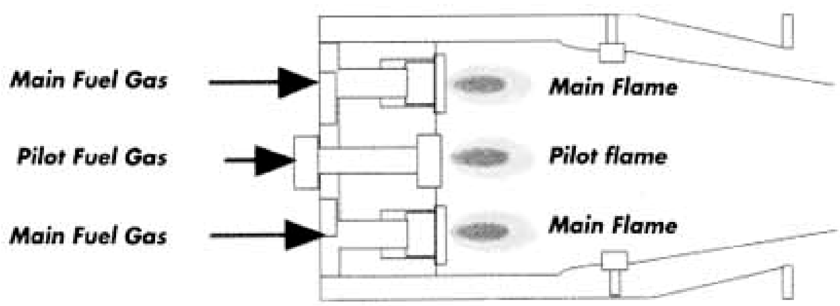

FIG 3.4: COMBUSTION CHAMBER

A type of combustion chamber is shown in Fig. 3.4. A pilot burner is used for maintaining the flame, or the main burner is composed by a multiple of single burners to adjust the number of burning flames in accordance with the output, but it is not able to follow a rapid output change, resulting in flame-out or unstable combustion. Compressed air enters through the perforations. Exhaust gases exit from the other side. In this type of combustor the air leaving the compressor is split into a number of split streams, each supplying a separate chamber. These chambers are spaced around the shaft connecting the compressor and the turbine, each chamber having its own fuel jet fed from a common supply line. This arrangement was well suited to engines with centrifugal compressors, where the flow was divided into separate streams in the diffuser. But in the aircraft applications, however this can type of combustor is undesirable in terms of weight, volume and frontal area and is no longer used in current designs. Small gas turbines, such as auxiliary power units and those proposed for vehicles, have often been designed with a single combustion can.

The ideal configuration of combustor in terms of compact dimensions is the annular combustor, in which maximum use is made of the space available within a specified diameter; this should reduce the pressure loss and result in an engine of minimum diameter. Large industrial gas turbines, where the space required by the combustion system is less critical, have used one or two large cylindrical combustion chambers; these were mounted vertically and are often referred as silos-type combustors because of their size and physical resemblance to silos.

3.1.3 THE TURBINE

The gas turbine in its most common form is a heat engine operating through a series of processes. These processes consist of compression of air taken from the atmosphere, increasing of gas temperature by the constant-pressure combustion of fuel in the air, expansion of the hot gases, and finally, discharging of the gases to atmosphere, in a continuous flow process. It is similar to the gasoline and Diesel engines in its working medium and internal combustion, but is like the steam turbine in the steady flow of the working medium. The compression and expansion processes are both carried out by means of rotating elements in which the energy transfer between fluid and rotor is affected by means of kinetic action, rather than by positive displacement as in reciprocating machinery.

Energy is added to the gas stream in the combustor, where air is mixed with fuel and ignited. Combustion increases the temperature, velocity and volume of the gas flow. This is directed through a nozzle over the turbine's blades, spinning the turbine and powering the compressor. Energy is extracted in the form of shaft power, compressed air and thrust, in any combination, and used to power aircraft, trains, ships, generators, and even tanks.

Gas turbines move relatively large quantities of air through the cycle at very high velocities. Among the mechanical characteristics of gas turbine engines are very smooth operation and absence of vibration due to reciprocating action. The high rotational speeds utilized require very accurate rotor balancing to avoid damaging vibration. Rotor parts are highly stressed with low factors of safety. Blades are very finely tuned to avoid resonant vibration. Gas turbines have relatively few moving (and no sliding) parts and are not subjected to vibratory forces. As a result, they are highly reliable when properly designed and developed.

3.1.3.1 OPEN CYCLE GAS TURBINE

Gas turbines usually operate on an open cycle. Fresh air at ambient conditions is drawn into the compressor, where its temperature and pressure are raised. The high-pressure air proceeds into the combustion chamber, where the fuel is burned at constant pressure. The resulting high-temperature gases then enter the turbine, where they expand to the atmospheric pressure through a row of nozzle vanes. Expansion causes the turbine blade to spin, which then turns a shaft. The shaft work thus generated drives the auxiliaries which includes compressor, generators etc. if electricity is to be produced. The exhaust gases leaving the turbine in the open cycle are not re-circulated. The schematic diagram of the open cycle gas turbine is shown in Fig. 3.5.

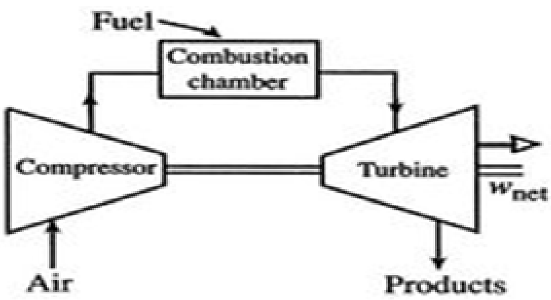

FIG. 3.5: OPEN CYCLE GAS TURBINE

3.1.3.2 CLOSED CYCLE GAS TURBINE

The open gas-turbine cycle can be modelled as a closed cycle by utilizing the air-standard assumptions. Here the compression and expansion process remain the same, but a constant-pressure heat-rejection process to the ambient air replaces the combustion process. The ideal cycle that the working fluid undergoes in this closed loop is the Brayton cycle, which is made up of four internally reversible processes. Using a closed cycle for the gas turbine develops the possibility of using a high pressure (and hence a high gas density) throughout the cycle, which would result in a reduced size of turbo-machinery for a given output. The schematic diagram of the closed cycle gas turbine is shown in Fig. 3.6.

The closed cycle open up the possibilities of the use of gases other than air having more desirable thermal properties. The monatomic gas such as helium which has the high value of specific heat can be used as working fluid. The better heat transfer characteristics of helium means that the size of the heat-exchanger and pre-cooler can be about half that of units designed for use with air.

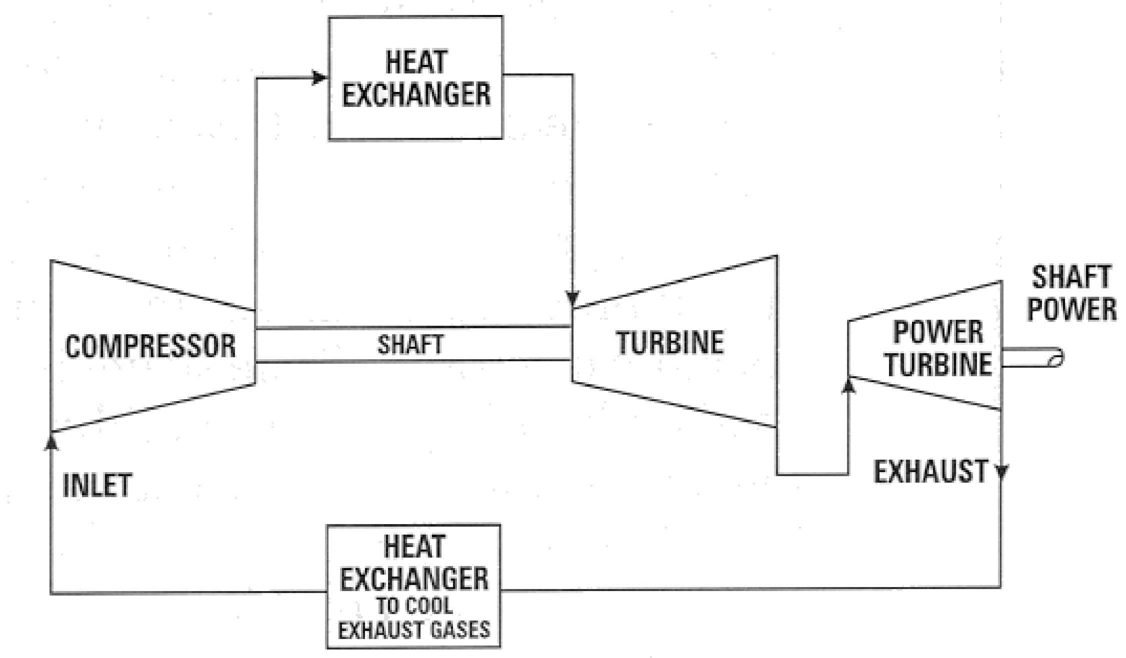

FIG. 3.6: CLOSED CYCLE GAS TURBINE

3.1.4 HEAT EXCHANGER

The temperature of gases leaving the turbine at the end of expansion is very high. Part of their heat content can be utilized to preheat the compressed air before it reaches the combustion chamber. This reheating is done in counter-flow heat exchanger. With heat-exchanger, there is no change in the compressor work, turbine work and network done. However, there is substantial reduction in the quantity of fuel required and this aspect results in the increase in the thermal efficiency. The arrangement of gas turbine employing heat exchanger is shown in Fig. 3.6. The efficiency of a regenerator is defined as,η_{EX}.

$$\eta_{EX} = \frac{actual\ heat\ transfer}{maximum\ possible\ heat\ transfer\ from\ gases}$$

3.1.5 INTERCOOLER

The power output of gas turbine can be increased by inter-cooling. The compressed air from low pressure compressor during delivery to high pressure compressor is cooled in the intercooler. Therefore the compression is preformed in two stages. The compressed cooled air has lesser volume, enabling air to be compressed in a smaller compressor with less expenditure of energy.

Clearly the work required for compression is reduced with intercooler. The heat supplied with inter-cooling is more than that with the heat supplied in single stage compression. The net output is also increased but thermal efficiency falls due to increased heat supply.

3.2 IDEAL OPERATING CYCLE (BRAYTON CYCLE)

The Brayton cycle (or Joule cycle) represents the operation of a gas turbine engine. The cycle consists of four processes, as shown in figure alongside a sketch of an engine:

- a - b Adiabatic and reversible compression in the inlet and compressor.
- b - c Constant pressure fuel combustion (idealized as constant pressure heat addition).
- c - d Adiabatic and reversible expansion in the turbine and exhaust nozzle, with which we
    1. take some work out of the air and use it to drive the compressor, and

2. take the remaining work out and use product of combustion process to produce shaft work turn a generator for electrical power generation.

- d - a Cool the air at constant pressure back to its initial condition.

The line diagram and P-V diagram of the gas turbine are shown in Fig. 3.7 and Fig. 3.8 respectively.

Air-standard assumptions: Assumptions that the compression and expansion processes are adiabatic (insulated) and reversible (isentropic), that there is no pressure drop during the heat addition process, and that the pressure leaving the turbine is equal to the pressure entering the compressor.

Internally reversible processes: Thermodynamics states that, for given temperature limits, a completely reversible cycle has the highest possible efficiency and specific work output, reversibility being both mechanical and thermal. Mechanical reversibility is a succession of states in mechanical equilibrium, i.e. fluid motion without friction, turbulence, or free expansion

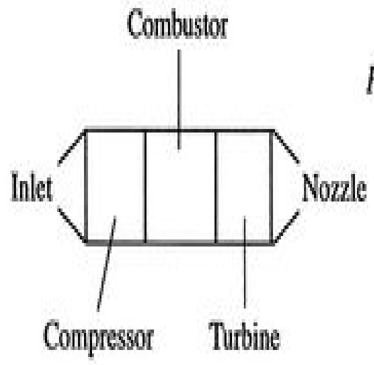

FIG 3.7: LINE DIAGRAM OF GAS TURBINE

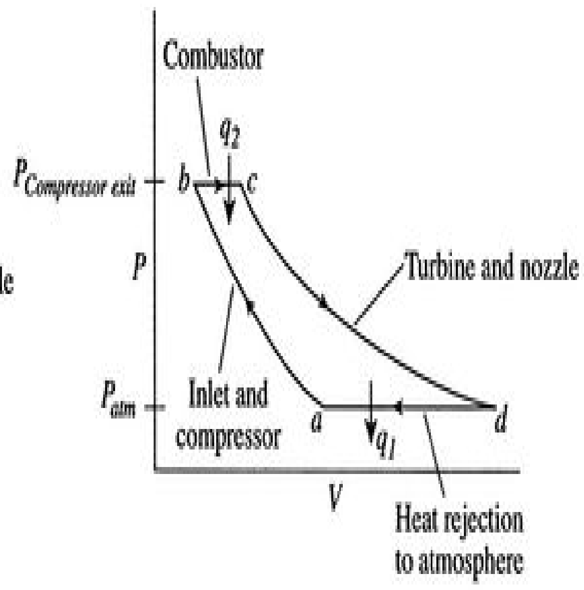

FIG 3.8: P-V DIAGRAM OF IDEAL BRAYTON CYCLE

. Thermal reversibility is a consequence of the Second Law of thermodynamics, which states that heat must be added only at the maximum temperature of the cycle and rejected at the minimum temperature.

Isentropic: Processes being done reversibly and adiabatically.

3.2.1 MATHEMATICAL TREATMENT OF BRAYTON CYCLE

The T-S and P-V diagrams of an ideal Brayton cycle are shown in Fig. 3.9 and Fig. 3.10 respectively. All four processes of the Brayton cycle are executed in steady flow devices so they should be analyzed as steady-flow processes.

When the changes in kinetic and potential energies are neglected, the energy balance for a steady-flow process can be express, on a unit-mass basis, as

$$(q_{in} - q_{out}) + (w_{in} - w_{out}) = (h_{out} - h_{inlet})$$

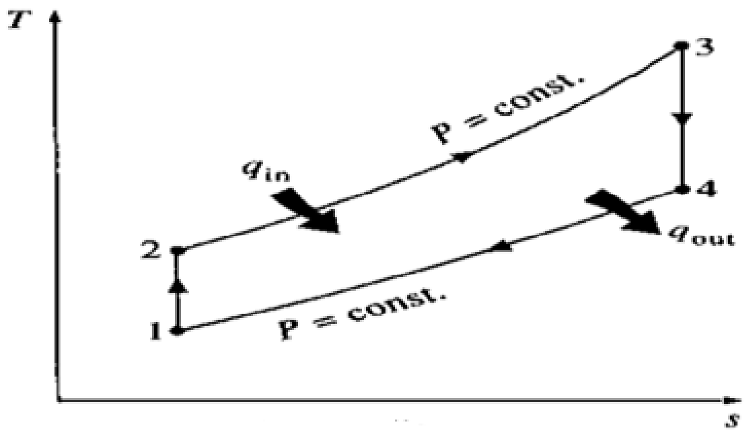

FIG. 3.9: T-S DIAGRAM OF BRAYTON CYCLE

Therefore, heat transfers to and from the working fluid are

$$q_{in} = h_3 - h_2 = C_p\,(T_3 - T_2)$$

$$q_{out} = h_4 - h_1 = C_p\,(T_4 - T_1)$$

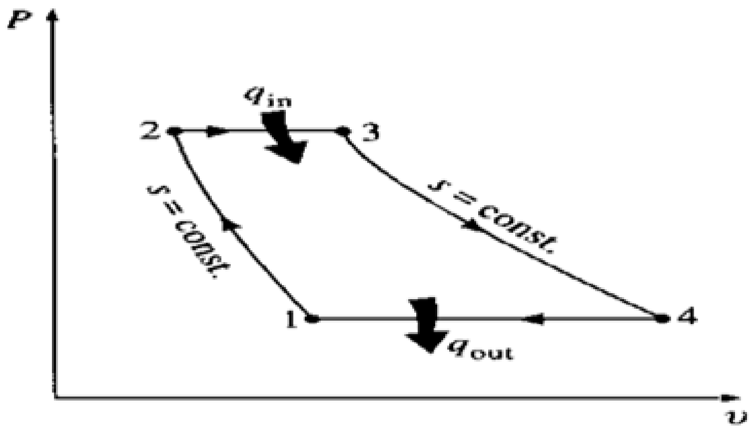

FIG. 3.10: P-V DIAGRAM OF BRAYTON CYCLE

Then the thermal efficiency of the ideal Brayton cycle under the air-standard assumptions becomes

$$\eta_{th} = \frac{w_{net}}{q_{in}} = 1 - \frac{q_{out}}{q_{in}} = 1 - \frac{C_p(T_3 - T_2)}{C_p(T_4 - T_1)} = 1 - \frac{T_1\left(\frac{T_4}{T_1} - 1\right)}{T_2\left(\frac{T_3}{T_2} - 1\right)}$$

Processes 1-2 and 3-4 are isentropic, and $P_2 = P_3$ and $P_4 = P_1$. Thus

$$\frac{T_2}{T_1} = \left(\frac{P_2}{P_1}\right)^{\frac{k-1}{k}} = \left(\frac{P_3}{P_4}\right)^{\frac{k-1}{k}} = \frac{T_3}{T_4}$$

Substituting these equations into the thermal efficiency relation and simplifying give the thermal efficiency as

$$\eta_{th} = 1 - \frac{1}{\left(r_p\right)^{\frac{k-1}{k}}}$$

where

$$r_p = \frac{P_2}{P_1}$$

is the pressure ratio and k is the specific heat ratio. Under the cold-air assumptions, the thermal efficiency of an ideal Brayton cycle depends on the pressure ratio of the gas turbine and the specific heat ratio of the working fluid (if different from air). The thermal efficiency increases with both of these parameters, which is also the case for actual gas turbines.

3.3 DEVIATION OF ACTUAL GAS-TURBINE CYCLES FROM IDEALIZED ONE:

The actual gas turbine cycle differs from the ideal Brayton cycle. Some pressure drop during the heat addition and rejection processes is unavoidable. The actual work input to the compressor will be more, and the actual work output from the turbine will be less because of irreversibility's. The deviation of actual compressor and turbine behavior from the idealized isentropic behaviour can be accurately accounted for by utilizing the adiabatic efficiencies of the turbine and compressor defined as

$$\eta_T = \frac{w_a}{w_s} = \frac{h_3 - h_{4a}}{h_3 - h_{4s}}$$

$$\eta_C = \frac{w_s}{w_a} = \frac{h_1 - h_{2s}}{h_1 - h_{2a}}$$

where states 2a and 4a are the actual exit states of the compressor and the turbine, respectively, and 2s and 4s are the corresponding states for the isentropic case.

3.3.1 THE BRAYTON CYCLE WITH REGENERATION

In gas-turbine engines, the temperature of the exhaust gas leaving the turbine is often considerably higher than the temperature of the air leaving the compressor. Therefore, the high-pressure air leaving the compressor can be heated by transferring heat to it from the hot exhaust gases in a counter-flow heat exchanger, which is also known as a regenerator or recuperator. Gas turbine heat exchangers are usually constructed as shell-and-tube type heat exchangers using very small diameter tubes, with the high pressure air inside the tubes and low pressure exhaust gas in multiple passes outside the tubes. The thermal efficiency of the Brayton cycle increases as a result of regeneration since the portion of energy of the exhaust gases that is normally rejected to the surroundings is now used to preheat the air entering the combustion chamber. This, in turn, decreases the heat input (thus fuel) requirements for the same net work output. Note, however, that the use of a regenerator is recommended only when the turbine exhaust temperature is higher than the compressor exit temperature. Otherwise, heat will flow in the reverse direction (to the exhaust gases), decreasing the efficiency. This situation is encountered in gas turbines operating at very high-pressure ratios.

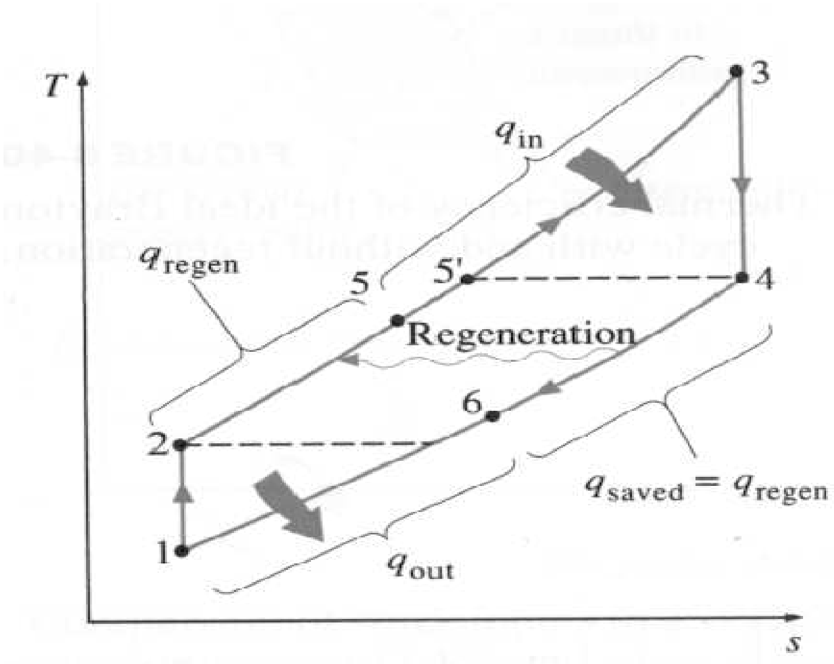

FIG 3.11: T-S DIAGRAM OF A BRAYTON CYCLE WITH REGENERATION

A regenerator with a higher effectiveness will save a greater amount of fuel since it will preheat the air to a higher temperature prior to combustion. However, achieving a higher effectiveness requires the use of a larger regenerator, which carries a higher price tag and causes a larger pressure drop because shaft horsepower is reduced. Pressure drop through the regenerator or recuperator is important and should be kept as low as practical on both sides. Therefore, the use of a regenerator with a very high effectiveness cannot be justified economically unless the savings from the fuel costs exceed the additional expenses involved. The effectiveness of most regenerators used in practice is below 0.85. The thermal efficiency of an ideal Brayton cycle with regeneration depends on the ratio of the minimum to maximum temperatures as well as the pressure ratio. Regeneration is most effective at lower pressure ratios and low minimum-to-maximum temperature ratios.

3.3.2 BRAYTON CYCLE WITH INTERCOOLING, REHEATING AND REGENERATION

The net work of a gas-turbine cycle is the difference between the turbine work output and the compressor work input, and either decreasing the compressor work, or increasing the turbine work or both can increase it. Carrying out the compression process in stages and cooling the gas in between the lower and higher-pressure stages will decrease the work required to compress a gas between two specified pressures. This is called multistage compression with inter-cooling. As the number of stages is increased, the compression process becomes nearly isothermal at the compressor inlet temperature, and the compression work decreases.

Likewise, the work output of a turbine operating between two pressure levels can be increased by expanding the gas in stages and reheating it in between – that is; utilizing multistage expansion with reheating. This process involves dividing the turbine into two parts, a high-pressure and a low-pressure turbine. After the gas passes through the high-pressure turbine it is extracted from the turbine and admitted to a second combustor. Reheated gas flow into the low-pressure turbine, which may be on a separate shaft, or both turbines and the compressor, may be connected to a common shaft. In either case, the reheat process is thermodynamically the same. This is accomplished without raising the maximum temperature in the cycle. As the number of stages is increased, the expansion process becomes nearly isothermal. This is based on a simple principle: The steady-flow compression or expansion work is proportional to the specific volume of the fluid. Therefore, the specific volume of the working fluid should be as low as possible during a compression process and as high as possible during an expansion process. This is precisely what inter-cooling and reheating accomplish.

Combustion in gas turbines typically occurs at four times the amount of air actually needed for complete combustion to avoid excessive temperatures. Therefore, the exhaust gases are rich in oxygen, and reheating can be accomplished by simply spraying additional fuel into the exhaust gases between two expansion states.

The working fluid leaves the compressor at a lower temperature and the turbine at a higher temperature, when inter-cooling and reheating are utilized. This makes regeneration more attractive since a greater potential for regeneration exits. Also, the gases leaving the compressor can be heated to a higher temperature before they enter the combustion chamber because of the higher temperature of the turbine exhaust.

In Fig. 3.12 it is clear that the gas enters the first stage of the compressor and is compressed isentropically to an intermediate pressure and cooled at constant pressure. It is then compressed in the second stage isentropically to the final pressure. The gas now enters the regenerator, where it is heated at a constant pressure. In an ideal regenerator, the gas will leave the regenerator at the temperature of the turbine exhaust. The gas enters the first stage of the turbine and expands isentropically where it enters the reheater. It is reheated at constant pressure, where it enters the second stage of the turbine. The gas exits the turbine and enters the regenerator, where it is cooled at a constant pressure. The cycle is completed by cooling the gas to the initial state (or purging the exhaust gases).

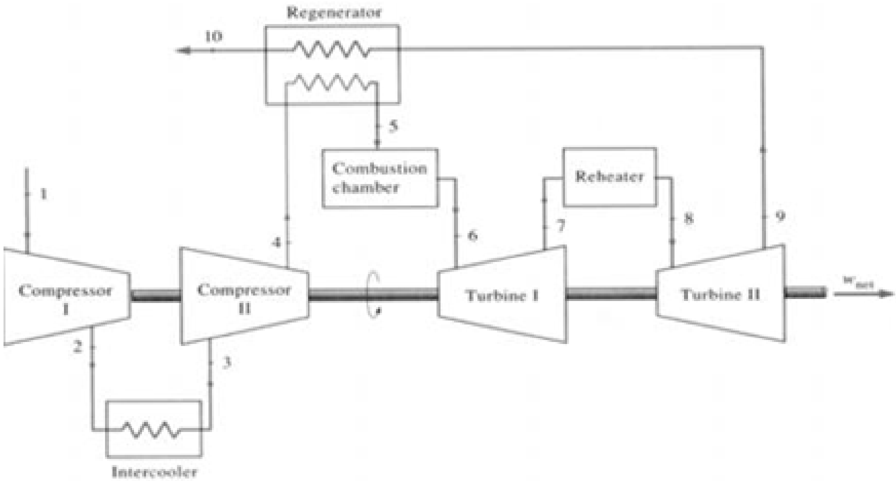

FIG 3.12: SCHEMATIC DIAGRAM FOR GAS TURBINE ENGINE WITH TWO-STAGE COMPRESSION WITH INTERCOOLING, TWO-STAGE EXPANSION WITH REHEATING AND REGENERATION.

In the analysis of the actual gas-turbine cycles, the irreversibility's that are present within the compressor, the turbine, and the regenerator as well as the pressure drops in the heat exchangers should be taken into consideration. The T-S diagram of a gas turbine engine with two-stage compression with intercooling, two-stage expansion with reheating and regeneration is shown in Fig. 3.13. it is clear from the figure that the heat which is going to be wasted is saved by using it to heat the compressed gases after second compression hence it reduces the amount of fuel used.

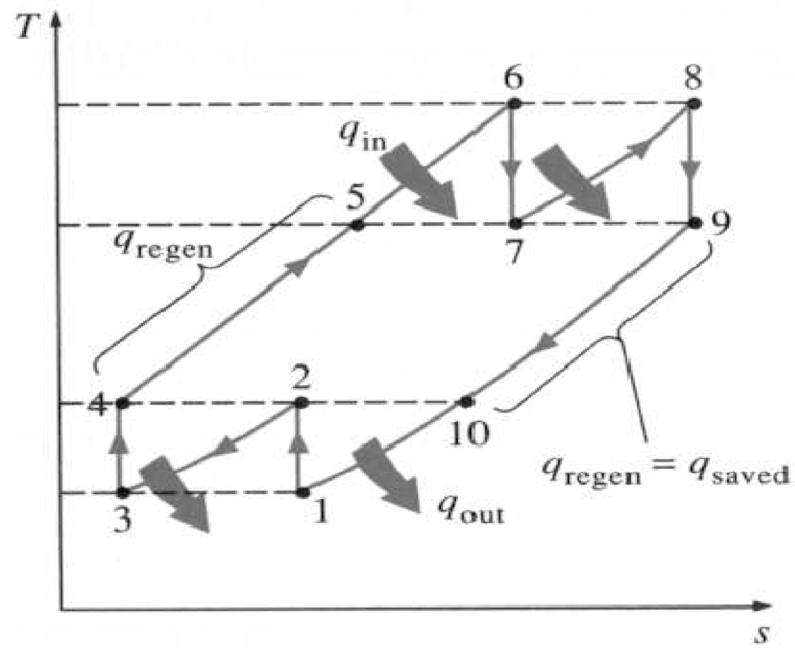

FIG 3.13: T-S DIAGRAM OF A GAS-TURBINE WITH INTERCOOLING, REHEATING AND REGENERATION

3.4 CYCLES AND CONFIGURATIONS

In the compressors and turbines, the flow is irreversible adiabatic and not isentropic. There occur losses in them. Similarly the heat exchanger and intercooler have pressure losses in them and these are not hundred percent efficient. In the present analysis, efficiencies and component losses are assumed to be known in advance. The temperature entropy diagram for the cycle changes, as we take into account the pressure loss and efficiencies of the various components constituting a particular arrangement. The various configurations that we had taken into account in this work are as follows as given in the reference paper.

3.4.1 1/C CONFIGURATION: The arrangement consists of a compressor, turbine and combustion chamber only. The arrangement and block diagram for the 1/C is shown in Fig. 4.1 and Fig. 4.2 respectively. There occurs a pressure loss in combustion chamber.

3.4.2 1/C/E CONFIGURATION: The configuration consists of a compressor, turbine, regenerator and combustion chamber. The arrangement and block diagram for the 1/C/E is shown in Fig. 4.3 and Fig. 4.4 respectively. In the heat exchanger there occurs a pressure loss both on the high pressure side and low pressure side.

3.4.3 1/LP CONFIGURATION: The arrangement and block diagram for the 1/LP is shown in Fig. 4.5 and Fig. 4.6 respectively**.** There occurs a pressure loss in the combustion chamber only. The configuration has a compressor, combustion chamber and two turbines, one designated as HP (high pressure) turbine and other as LP (low pressure) turbine. High pressure turbine drives the compressor and low pressure gives network output.

3.4.4 1/LP/E CONFIGURATION: The configuration consists of a compressor, combustion chamber, a high pressure turbine, a low pressure turbine and a regenerator. There occurs a pressure loss in the heat exchanger on both low pressure and high pressure side. The arrangement and block diagram for the 1/LP/E is shown in Fig. 4.7 and Fig. 4.8 respectively

CHAPTER 4 RELATIONS FOR DIFFERENT CONFIGURATIONS OF GAS TURBINE CYCLES

4.1 INTRODUCTION

Using temperature ratio of various components and their efficiencies, non-dimensional specific output and thermal efficiency are calculated. The same procedure is used for calculating the optimization constraints and inequality constraints which are expressed using non-dimensional temperature ratios, various component losses and efficiencies of regenerator, turbine, intercooler, combustion chambered compressor.

If the inlet conditions of working are given, the outlet conditions for each of the components can be determined. The parameters are pressure ratios, temperature ratios and component efficiencies. In the present analysis, efficiencies and pressure losses of each component are assumed to be known in advance. The temperature ratio for combustion chamber is calculated from compressor outlet temperature and turbine inlet temperature. The maximum temperature ratio is introduced and is defined as the ratio of turbine inlet temperature to ambient temperature.

In the derivations of the following relations assumptions made are:

1. Working fluid is perfect gas with constant specific heat.
2. The temperature ratio of cycle is constant.
3. The increase of mass flow rate due to addition of fuel and mechanical losses are neglected.

4.2 RELATIONS FOR 1/C CONFRIGUATION

The configuration consists of a compressor, combustion chamber and a turbine only. The constraint equations, the non-dimensional specific output and thermal efficiency are expressed in the form of the non-dimensional temperature ratios and component efficiencies. For the configuration 1/C, the arrangement of the system is shown in the Fig. 4.1.

The various temperature ratios are as follows:

$$\theta = \frac{maximum\ temperature\ of\ cycle}{temperature\ at\ inlet} = \frac{T_{max}}{T_{in}}$$

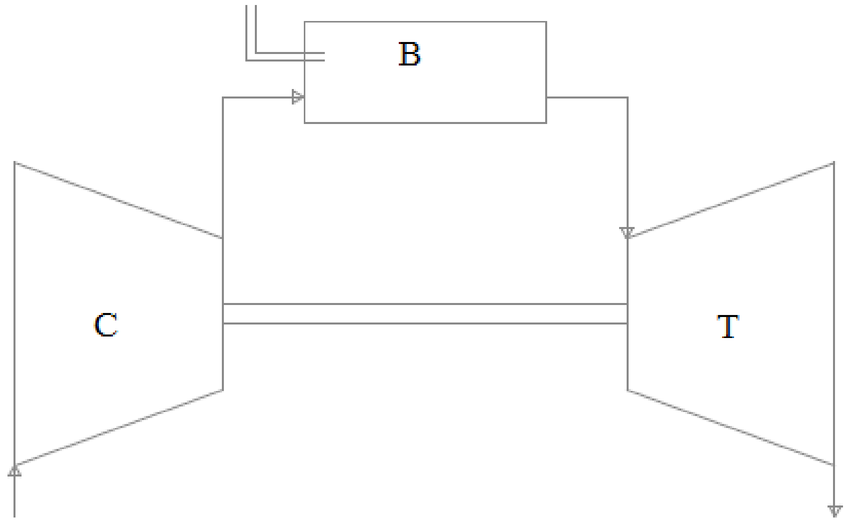

FIG. 4.1: ARRANGEMENT OF 1/C CONFIGURATION

it is also called as temperature ratio or cycle maximum temperature ratio. There are two design variables in this problem which are defined as θ_T and θ_C.

$$\theta_T = \frac{T_E}{T_{max}} = \frac{temperature\ at\ exhaust\ of\ turbine}{maximum\ temperature\ of\ cycle}$$

$$\theta_C = \frac{T_{out}}{T_{in}} = \frac{temperature\ at\ compressor\ outlet}{temperature\ at\ compressor\ inlet}$$

4.2.1 CONSTRAINTS:

1. Temperature at compressor outlet, $T_{out} \geq$ Temperature at compressor inlet, T_{in}

$$T_{out} \geq T_{in}$$

$$\frac{T_{out}}{T_{in}} \geq 1$$

$$\frac{T_{out}}{T_{in}} - 1 \geq 0$$

$$\theta_C - 1 \geq 0$$

2. Temperature at the exhaust of turbine = T_E

   Temperature at exhaust of turbine ≥ Temperature at inlet to the compressor

$$T_E \geq T_{in}$$

$$T_{in} \leq T_E$$

$$T_E - T_{in} \geq 0$$

$$\frac{T_E}{T_{in}} - 1 \geq 0$$

$$\frac{T_E\, T_{max}}{T_{max} T_{in}} - 1 \geq 0$$

$$\theta_T\ \theta - 1 \geq 0$$

3. Thermal efficiency should be greater than or equal to zero.

$$\eta_{th} \geq 0$$

For the configuration 1/C, the block diagram for the stationary gas turbine is shown in Fig. 4.2.

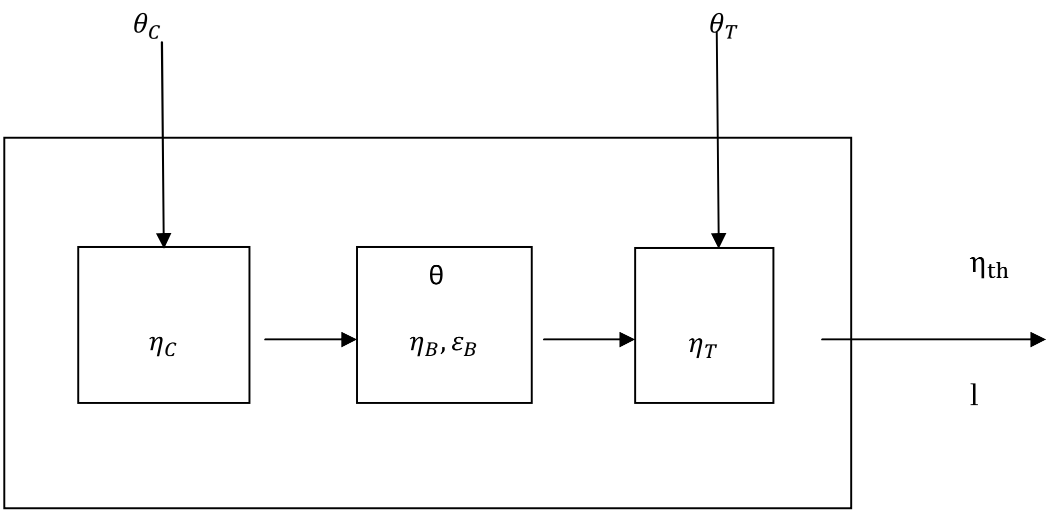

FIG. 4.2: BLOCK DIAGRAM FOR 1/C CONFIGURATION

4.2.2 NON-DIMENSIONAL SPECIFIC OUTPUT

Work done per cycle is given by

l = Turbine work output- compressor work input

$$= C_p\,(T_{max} - T_E) - C_p(T_{out} - T_{in})$$

$$= C_p\,T_{max}\left(1 - \frac{T_E}{T_{max}}\right) - C_p\,T_{in}(\frac{T_{out}}{T_{in}} - 1)$$

Non-dimensional Specific Output, I= $\frac{l}{C_p T_{in}}$

$$I = \frac{l}{C_p T_{in}} = \frac{C_p T_{max}}{C_p T_{in}}\left(1 - \frac{T_E}{T_{max}}\right) - \frac{C_p T_{in}}{C_p T_{in}}(\frac{T_{out}}{T_{in}} - 1)$$

$$I = \theta(1 - \theta_T) - (\theta_C - 1)$$

4.2.3 THERMAL EFFICIENCY

Thermal Efficiency, $\eta_{th} = \frac{Work\ output}{Heat\ released\ by\ combustion\ of\ fuel}$

Work Output = Turbine work – compressor work

Heat released by combustion of fuel= $\frac{heat\ supplied\ in\ combustion\ chamber}{efficiency\ of\ combustion\ chamber}$

Thermal efficiency = η_{th}

$$= \frac{C_P(T_{max} - T_E) - C_p(T_{out} - T_{in})}{\frac{C_P(T_{max} - T_{out})}{\eta_B}}$$

$$= \eta_B \frac{C_P(T_{max} - T_E) - C_p(T_{out} - T_{in})}{C_P(T_{max} - T_{out})}$$

$$= \eta_B \frac{(T_{max} - T_E) - (T_{out} - T_{in})}{(T_{max} - T_{out})}$$

$$= \eta_B[\frac{(T_{max} - T_{out}) - (T_E - T_{in})}{(T_{max} - T_{out})}]$$

$$= \eta_B[1 - \frac{(T_E - T_{in})}{(T_{max} - T_{out})}]$$

$$= \eta_B[1 - \frac{\frac{T_E}{T_{max}} . \frac{T_{max}}{T_{in}} - 1}{\frac{T_{max}}{T_{in}} - \frac{T_{out}}{T_{in}}}]$$

$$\eta_{th} = \eta_B[1 - \frac{(\theta\theta_T - 1)}{(\theta - \theta_C)}]$$

4.3 RELATIONS FOR 1/C/E CONFIGURATION

In this arrangement, a regenerator is introduced in the configuration consisting of a combustion chamber, compressor and turbine. Arrangement for stationary gas turbine configuration 1/C/E is shown in Fig. 4.3. There are three design variables for scheme 1/C/E. these are θ_C, θ_E *and* θ_T.

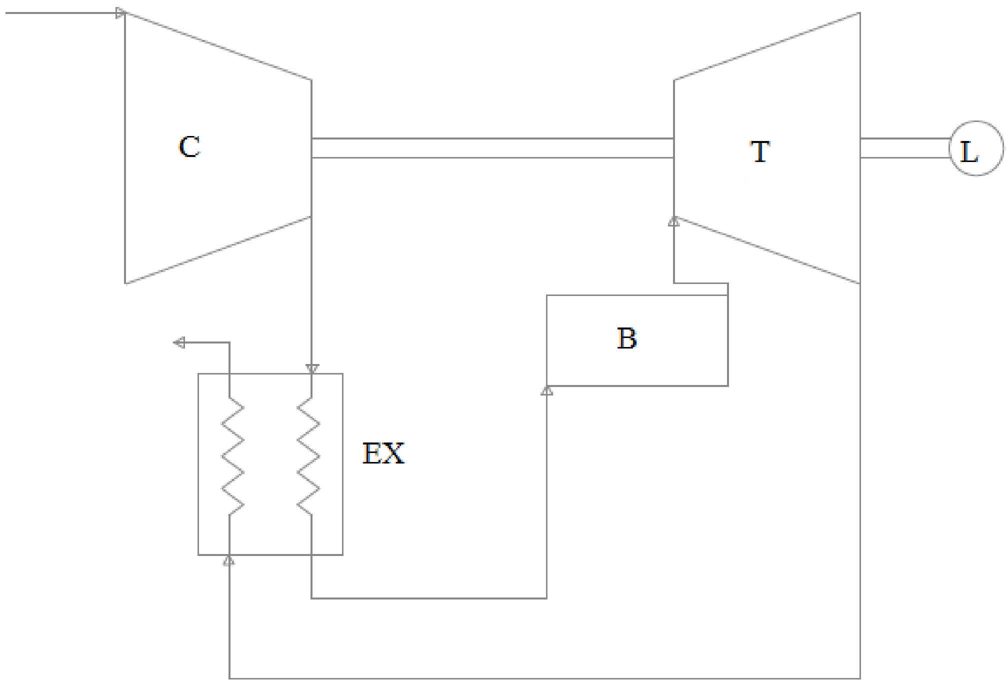

FIG. 4.3: ARRANGEMENT OF 1/C/E CONFIGURATION

$$\theta_C = \frac{T_{out}}{T_{in}} = \frac{Temperature\ at\ compressor\ outlet}{Temperature\ at\ compressor\ inlet}$$

$$\theta_E = \frac{T_{EX}}{T_{out}} = \frac{Temperature\ at\ regenerator\ outlet}{Temperature\ of\ air\ at\ the\ inlet\ of\ regenrator}$$

$$\theta_T = \frac{T_E}{T_{max}} = \frac{Temperature\ at\ exhaust\ of\ turbine}{Maximum\ temperature\ of\ cycle}$$

4.3.1 CONSTRAINTS:

1. Temperature at compressor outlet, $T_{out} \geq$ Temperature at compressor inlet, T_{in}

$$T_{out} \geq T_{in}$$

$$\frac{T_{out}}{T_{in}} \geq 1$$

$$\frac{T_{out}}{T_{in}} - 1 \geq 0$$

$$\theta_C - 1 \geq 0$$

2. Temperature at regenerator outlet, $T_{EX} \geq$ Temperature at regenerator inlet, T_{out}

$$T_{EX} \geq T_{out}$$

$$\frac{T_{EX}}{T_{out}} \geq 1$$

$$1 \leq \theta_E$$

3. Maximum temperature of cycle, $T_{max} \geq$ Temperature at regenerator outlet, T_{EX}

$$\frac{T_{EX}T_{out}}{T_{out}T_{in}} \leq \frac{T_{max}}{T_{in}}$$

$$\theta_E\theta_C \leq \theta$$

$$\theta - \theta_C\theta_E \geq 0$$

4. $\theta_T = \frac{T_E}{T_{max}} = \frac{Temperature\ at\ exhaust\ of\ turbine}{Maximum\ temperature\ of\ cycle} \geq 0$

5. Temperature at exhaust of turbine, $T_E \leq$ Maximum temperature of cycle, T_{max}

$$\theta_T = \frac{T_E}{T_{max}} \leq 1$$

Therefore, $$0 \leq \theta_T \leq 1$$

For the configuration 1/C/E, the block diagram for the stationary gas turbine is shown in Fig. 4.4.

4.3.2 NON-DIMENSIONAL SPECIFIC OUTPUT

Work done per cycle, l = turbine output – compressor work input

$$= C_p\,(T_{max} - T_E) - C_p(T_{out} - T_{in})$$

$$= C_p\,T_{max}\left(1 - \frac{T_E}{T_{max}}\right) - C_p\,T_{in}\left(\frac{T_{out}}{T_{in}} - 1\right)$$

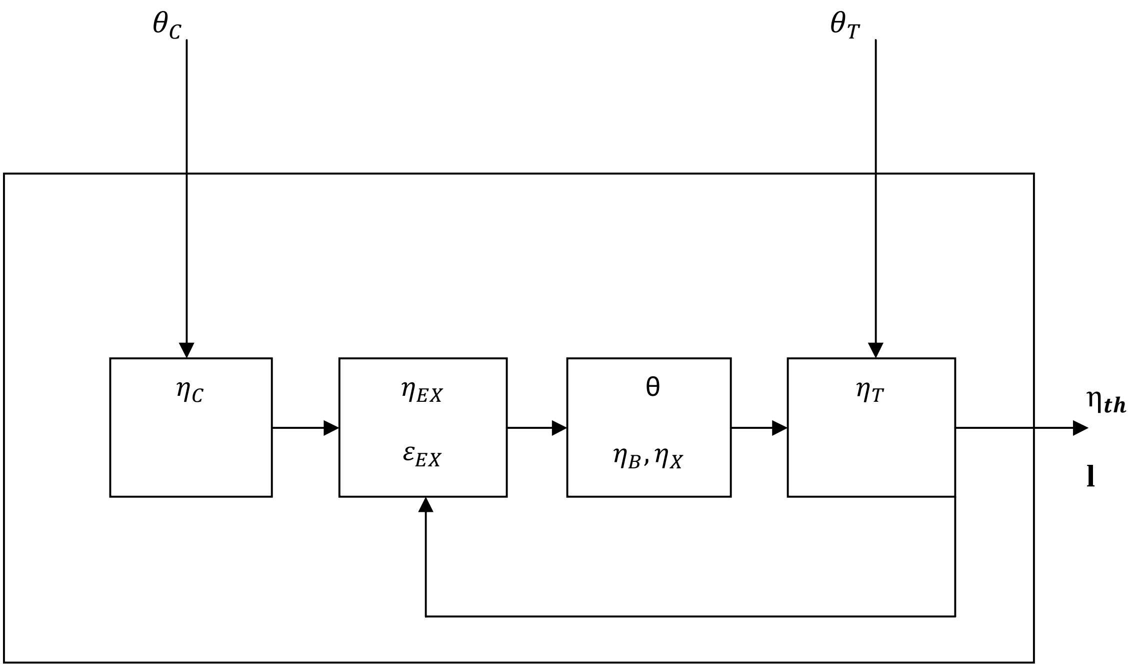

FIG. 4.4: BLOCK DIAGRAM FOR 1/C/E CONFIGURATION

Non-dimensional Specific Output, I= $\frac{l}{C_p T_{in}}$

$$I = \frac{l}{C_p T_{in}} = \frac{C_p T_{max}}{C_p T_{in}}\left(1 - \frac{T_E}{T_{max}}\right) - \frac{C_p T_{in}}{C_p T_{in}}\left(\frac{T_{out}}{T_{in}} - 1\right)$$

$$I = \theta(1 - \theta_T) - (\theta_C - 1)$$

4.3.3 THERMAL EFFICIENCY

Thermal Efficiency, $\eta_{th} = \frac{Work\ output}{Heat\ released\ by\ combustion\ of\ fuel}$

Work Output = Turbine work – compressor work

$$= C_p\,(T_{max} - T_E) - C_p(T_{out} - T_{in})$$

Heat released by combustion of fuel = $\frac{heat\ supplied\ in\ combustion\ chamber}{efficiency\ of\ combustion\ chamber}$

$$= \frac{C_p(T_{max} - T_{EX})}{\eta_B}$$

Thermal efficiency = η_{th}

$$= \frac{C_P(T_{max} - T_E) - C_p(T_{out} - T_{in})}{\frac{C_P(T_{max} - T_{EX})}{\eta_B}}$$

$$= \eta_B \frac{C_P(T_{max} - T_E) - C_p(T_{out} - T_{in})}{C_P(T_{max} - T_{EX})}$$

$$= \eta_B[\frac{(T_{max} - T_E) - (T_{out} - T_{in})}{(T_{max} - T_{EX})}]$$

$$= \eta_B[\frac{T_{max}\left(1 - \frac{T_E}{T_{max}}\right) - (\frac{T_{out}}{T_{in}} - 1)T_{in}}{T_{max} - T_{EX}}]$$

$$= \eta_B[\frac{T_{max}(1 - \theta_T) - T_{in}(\theta_C - 1)}{T_{max} - T_{EX}}]$$

dividing numerator and denominator by T_{in}

$$= \eta_B[\frac{\frac{T_{max}}{T_{in}}(1 - \theta_T) - \frac{T_{in}}{T_{in}}(\theta_C - 1)}{\frac{T_{max} - T_{EX}}{T_{in}}}]$$

$$= \eta_B [\frac{\theta(1-\theta_T) - (\theta_C - 1)}{\frac{T_{max}}{T_{in}} - \frac{T_{EX}.T_{out}}{T_{out}.T_{in}}}]$$

$$\eta_{th} = \eta_B [\frac{\theta(1-\theta_T) - (\theta_C - 1)}{\theta - \theta_C\theta_E}]$$

4.4 RELATIONS FOR 1/LP CONFIGURATION

The expansion is carried out in two stages. The high pressure turbine is used in driving the compressor. The work output is obtained from the low pressure turbine. Arrangement for stationary gas turbine configuration 1/C/E is shown in Fig. 4.5. The various temperature ratios are as follows:

$$\theta_C = \frac{T_{out}}{T_{in}} = \frac{Temperature\ at\ compressor\ outlet}{Temperature\ at\ compressor\ inlet}$$

$$\theta_E = \frac{T_{EX}}{T_{out}} = \frac{Temperature\ at\ regenerator\ outlet}{Temperature\ of\ air\ at\ the\ inlet\ of\ regenrator}$$

$$\theta_T = \frac{T_E}{T_{max}} = \frac{Temperature\ at\ exhaust\ of\ turbine}{Maximum\ temperature\ of\ cycle}$$

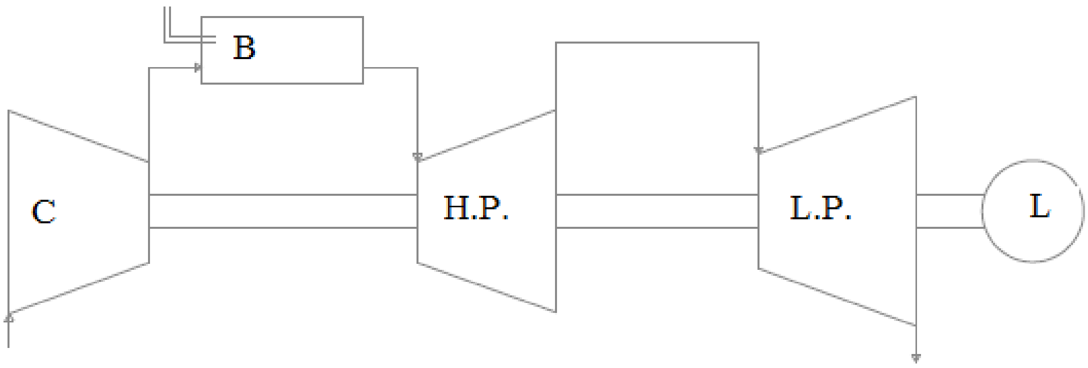

FIG. 4.5: ARRANGEMENT OF 1/LP CONFIGURATION

4.4.1 CONSTRAINTS:

There are three input variables. θ_{HT} is temperature ratio of high pressure turbine. θ_{LT} is the temperature ratio of the low pressure turbine and θ_C is temperature ratio in the compressor.

$$\theta_{HT} = \frac{Temperature\ at\ outlet\ of\ the\ high\ pressure\ turbine}{Temperature\ at\ inlet\ to\ the\ high\ pressure\ turbine} = \frac{T_{E1}}{T_{max}}$$

$$\theta_{LT} = \frac{Temperature\ at\ outlet\ of\ the\ low\ pressure\ turbine}{Temperature\ at\ inlet\ to\ the\ low\ pressure\ tubine} = \frac{T_e}{T_{E1}}$$

1. Temperature at compressor outlet, T_{out} $\geq$ Temperature at compressor inlet, T_{in}

$$0 \leq \theta_C \leq 1$$

2. Temperature at outlet of high pressure turbine, T_{E1} $\leq$ Temperature at inlet to the low pressure turbine, T_{max}

$$T_{E1} \leq T_{max}$$

$$\frac{T_{E1}}{T_{max}} \leq 1$$

$$0 \leq \theta_{HT} \leq 1$$

3. Temperature at outlet of low pressure turbine, T_e $\leq$ Temperature at inlet to the low pressure turbine, T_{E1}

$$T_e \leq T_{E1}$$

$$\frac{T_e}{T_{E1}} \leq 1$$

$$0 \leq \theta_{LT} \leq 1$$

4.4.2 NON-DIMENSIONAL SPECIFIC OUTPUT

The block diagram for the configuration 1/LP is shown in Fig. 4.6.

Work done = network output of the L.P. turbine

$$l = C_P(T_{E1} - T_e)$$

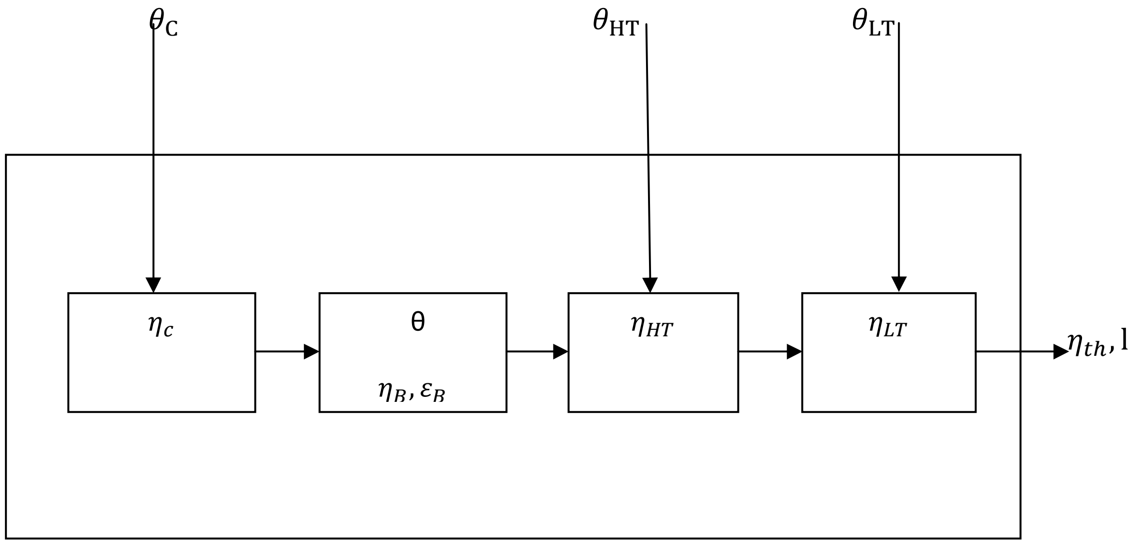

FIG. 4.6: BLOCK DIAGRAM FOR 1/LP CONFIGURATION

Non-dimensional Specific Output, I = $\frac{l}{C_p T_{in}}$

$$I = \frac{C_P(T_{E1} - T_e)}{C_p T_{in}}$$

$$I = \frac{(T_{E1} - T_e)}{T_{in}}$$

$$I = \frac{T_{E1}}{T_{in}}\left(1 - \frac{T_e}{T_{E1}}\right)$$

$$I = \frac{T_{max}}{T_{in}}\frac{T_{E1}}{T_{max}}\left(1 - \frac{T_e}{T_{E1}}\right)$$

$$I = \theta\ \theta_{HT}(1 - \theta_{LT})$$

4.4.3 THERMAL EFFICIENCY

Thermal Efficiency, $\eta_{th} = \frac{work\ output\ of\ L.P.turbine}{Energy\ supplied}$

Work output of L.P. turbine = $C_P(T_{E1} - T_e)$

Energy supplied to the compressor = $\frac{heat\ supplied\ in\ combustion\ chamber}{efficiency\ of\ combustion\ chamber}$

$$= \frac{C_p(T_{max} - T_{out})}{\eta_B}$$

Thermal efficiency, η_{th}

$$= \frac{C_P(T_{E1} - T_e)}{\frac{C_p(T_{max} - T_{out})}{\eta_B}}$$

$$= \frac{\eta_B(T_{E1} - T_e)}{(T_{max} - T_{out})}$$

$$= \eta_B \frac{T_{E1}(1 - \frac{T_e}{T_{E1}})}{(T_{max} - T_{out})}$$

$$= \eta_B \frac{\frac{T_{E1}}{T_{in}}\frac{T_{max}}{T_{max}}(1 - \frac{T_e}{T_{E1}})}{\frac{T_{max}}{T_{in}} - \frac{T_{out}}{T_{in}}}$$

$$\eta_{th} = \eta_B \frac{\theta\theta_{HT}(1 - \theta_{LT})}{\theta - \theta_C}$$

4.5 RELATIONS FOR 1/LP/E CONFIGURATION

In this arrangement there are two turbines and there is heat exchanger which is connected to the low pressure turbine stage. The arrangement for 1/LP/E configuration is shown in Fig. 4.7. The various temperature ratios are as follows:

$$\theta_C = \frac{T_{out}}{T_{in}} = \frac{Temperature\ at\ compressor\ outlet}{Temperature\ at\ compressor\ inlet}$$

$$\theta_E = \frac{T_{EX}}{T_{out}} = \frac{Temperature\ at\ regenerator\ outlet}{Temperature\ of\ air\ at\ the\ inlet\ of\ regenrator}$$

$$\theta_T = \frac{T_E}{T_{max}} = \frac{Temperature\ at\ exhaust\ of\ turbine}{Maximum\ temperature\ of\ cycle}$$

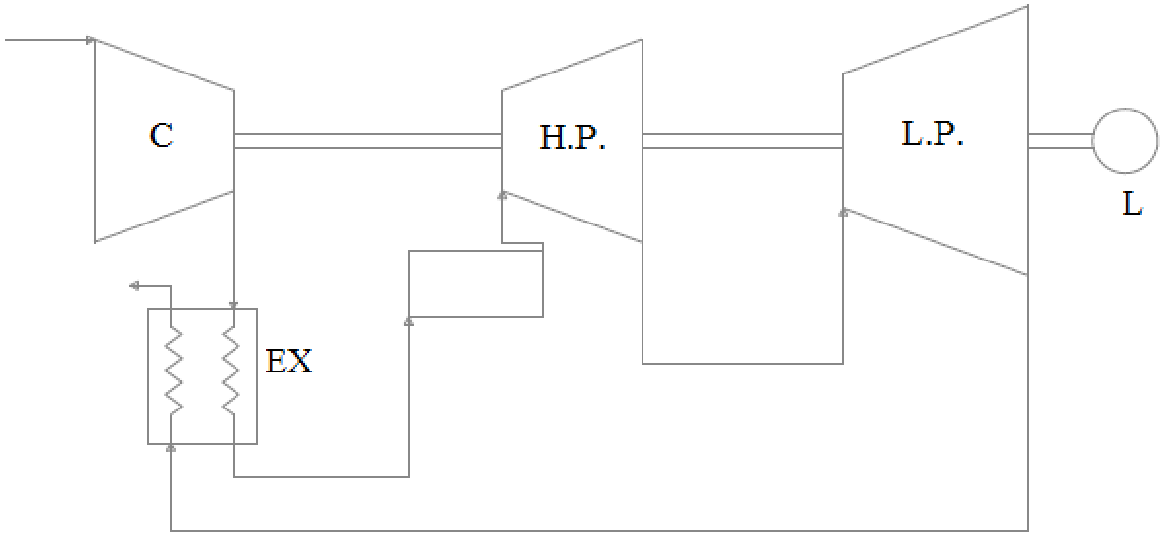

FIG. 4.7: ARRANGEMENT OF 1/LP/E CONFIGURATION

4.5.1 CONSTRAINTS

There are three input variables. θ_{HT} is temperature ratio of high pressure turbine. θ_{LT} is the temperature ratio of the low pressure turbine and θ_C is temperature ratio in the compressor.

$$\theta_{HT} = \frac{Temperature\ at\ outlet\ of\ the\ high\ pressure\ turbine}{Temperature\ at\ inlet\ to\ the\ high\ pressure\ turbine}$$

$$\theta_{HT} = \frac{T_{E1}}{T_{max}}$$

$$\theta_{LT} = \frac{Temperature\ at\ outlet\ of\ the\ low\ pressure\ turbine}{Temperature\ at\ inlet\ to\ the\ low\ pressure\ tubine}$$

$$\theta_{LT} = \frac{T_e}{T_{E1}}$$

1. Temperature at compressor outlet, $T_{out} \geq$ Temperature at compressor inlet, T_{in}

$$T_{out} \geq T_{in}$$

$$\frac{T_{out}}{T_{in}} \geq 1$$

$$\theta_C \geq 1$$

2. Temperature at regenerator outlet, $T_{EX} \geq$ Temperature at regenerator inlet, T_{out}

$$T_{EX} \geq T_{out}$$

$$\frac{T_{EX}}{T_{out}} \geq 1$$

$$\theta_E \geq 1$$

3. $\theta \geq \theta_E$
4. Temperature at outlet of high pressure turbine, $T_{E1} \leq$ Temperature at inlet to the low pressure turbine, T_{max}

$$T_{E1} \leq T_{max}$$

$$\frac{T_{E1}}{T_{max}} \leq 1$$

$$0 \leq \theta_{HT} \leq 1$$

5. Temperature at outlet of low pressure turbine, $T_e \leq$ Temperature at inlet to the low pressure turbine, T_{E1}

$$T_e \leq T_{E1}$$

$$\frac{T_e}{T_{E1}} \leq 1$$

$$0 \leq \theta_{LT} \leq 1$$

4.5.2 NON-DIMENSIONAL SPECIFIC OUTPUT

The block diagram for the configuration 1/LP/E is shown in Fig. 4.8.

Work done, l = network output of the L.P. turbine

$$l = C_P(T_{E1} - T_e)$$

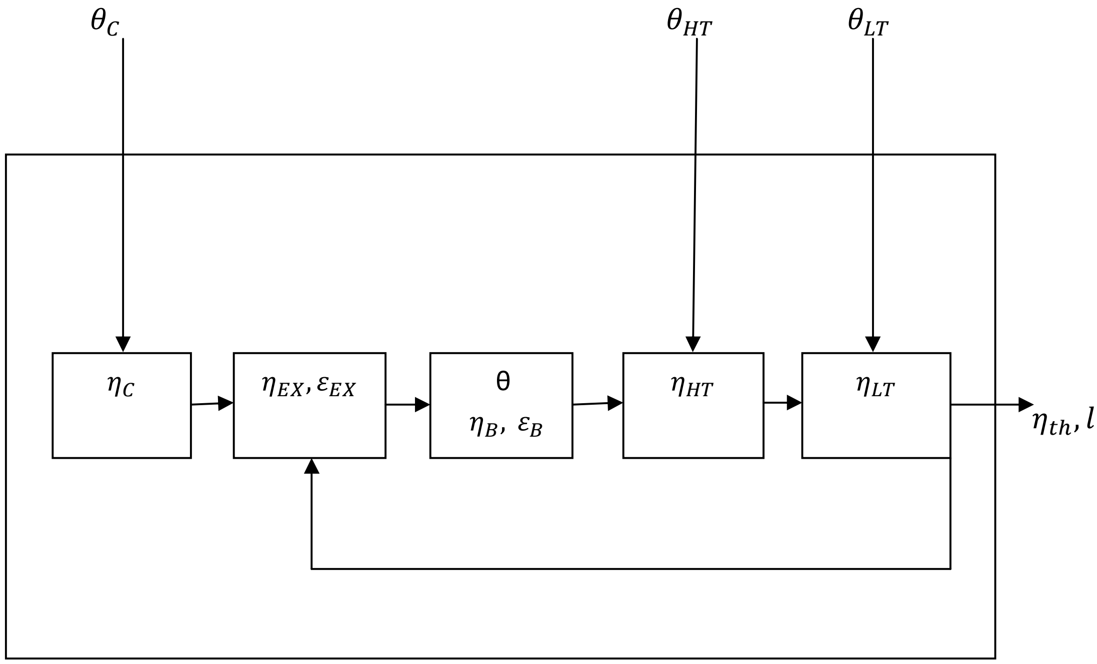

FIG. 4.8: BLOCK DIAGRAM FOR 1/LP/E CONFIGURATION

Non-dimensional Specific Output, $I = \frac{l}{C_P T_{in}}$

$$= \frac{C_P(T_{E1} - T_e)}{C_P T_{in}}$$

$$= \frac{(T_{E1} - T_e)}{T_{in}}$$

$$= \frac{T_{E1}}{T_{in}}\left(1 - \frac{T_e}{T_{E1}}\right)$$

$$= \frac{T_{max}}{T_{in}}\frac{T_{E1}}{T_{max}}\left(1 - \frac{T_e}{T_{E1}}\right)$$

$$I = \theta\ \theta_{HT}(1 - \theta_{LT})$$

4.5.3 THERMAL EFFICIENCY

Thermal Efficiency, $\eta_{th} = \frac{work\ output\ of\ L.P.turbine}{Energy\ supplied}$

Work output of L.P. turbine = $C_P(T_{E1} - T_e)$

Energy supplied to the compressor = $\frac{heat\ supplied\ in\ combustion\ chamber}{efficiency\ of\ combustion\ chamber}$

$$= \frac{C_p(T_{max} - T_{E1})}{\eta_B}$$

where T_{E1} is the temperature of the air leaving the heat exchanger and entering the combustion chamber.

$$= \frac{C_P(T_{E1} - T_e)}{\frac{C_p(T_{max} - T_{E1})}{\eta_B}}$$

$$= \frac{\eta_B(T_{E1} - T_e)}{(T_{max} - T_{E1})}$$

$$= \eta_B \frac{T_{E1}\left(1 - \frac{T_e}{T_{E1}}\right)}{(T_{max} - T_{E1})}$$

$$= \eta_B \frac{\frac{T_{E1}}{T_{in}}\frac{T_{max}}{T_{max}}(1 - \frac{T_e}{T_{E1}})}{\frac{T_{max}}{T_{in}} - \frac{T_{out}}{T_{in}}\frac{T_{E1}}{T_{out}}}$$

$$\eta_{th} = \eta_B \frac{\theta\theta_{HT}(1 - \theta_{LT})}{\theta - \theta_C\theta_E}$$

CHAPTER 5 OPTIMIZATION TECHNIQUES

5.1 OPTIMIZATION

Optimization is the art of obtaining best results under given circumstances. In an optimization problem one seeks to maximize or minimize a specific quantity called the objective, which depends on a finite number of (input) variables. These variables may be independent of one another or they may be related through one or more constraints. In engineering design activities, engineers have to take many technological and managerial decisions at several stages. The objective is to maximize desired benefit or minimize the effort required. The optimization methods are also known as mathematical programming techniques.

There may be more than one acceptable design and the purpose of optimization is to choose the best on out of the many acceptable design variables. Optimization problem is generally stated by specifying the constraints, objective functions and design vector.

5.1.1 DESIGN VARIABLES

An engineering system is described by a set of quantities, which are viewed as variables during the design process. Some quantities are usually fixed at outset and are called pre-assigned parameters. All other quantities are treated as variables in design process and are called design or decision vectors.

The choice of the important design variable is an optimization problem largely depends on the user and his experience. However, it is important to understand that the efficiency and speed of optimization technique depend to a large extent, on the number of chosen design variables. Thus by selectively choosing the design variables, the efficiency of the optimization technique can be increased. The first thumb rule of the formulation of optimization problem is to choose as little design variables as possible.

5.1.2 CONSTRAINTS

Constraints are basically limitations imposed upon the value of the design variable. There may be both equality as well as inequality constraints. The design variables are not chosen arbitrarily. They have to satisfy certain specified functional and other requirements. These restrictions must be satisfied in order to produce an acceptable design called design constraints. The constraints which represent limitations on the behaviour or performance of system are termed as behavior or functional constraints. Constraints depending upon physical limitations are called side constraints. Mathematically, there are usually two types of constraints which are as follows:

5.1.2.1 EQUALITY CONSTRAINT

Equality constraints state that the relationships should exactly match a resource value. Equality constraints are usually more difficult to handle and therefore, need to be avoided wherever possible. Thus, the second thumb rule in the formulation of optimization problem is that the number of complex equality constraints should be kept as low as possible.

5.1.2.2 INEQUALITY CONSTRAINT

Inequality constraints state that the relationships among design variables are greater than, smaller than or equal to a resource value.

5.1.3 OBJECTIVE FUNCTION

The criterion with respect to which design is optimized when expressed as function of design variables is known as objective function. Objective function depends upon nature of the problem. If any of the functions among objective and constraint functions are non-liner, the problem is called a non-liner programming problem. The choice of the objective function is governed by nature of the problem. Thus the selection of the objective function is one of the most important decisions in the whole optimum design process. In some situations, there may be more than one objective function to be satisfied simultaneously. An optimization problem involving multiple objective functions is known as a multi-objective programming problem.

In general, the objective function can be of two types, either the objective function is to be maximized or to be minimized. But, the optimization methods are usually either for minimization problem or for maximization problem. If the method/design is developed for solving a minimization problem, it can also be used to solve a maximization problem by simply multiplying the objective function by – (minus) and vice-versa.

5.2 FORMULATION OF OPTIMIZATION PROBLEM

The purpose of the formulation procedure is to create a mathematical model of the optimal problem, which then can be solved using an optimization technique. The following figure shows an outline of the steps usually involved in an optimal problem formulation process.

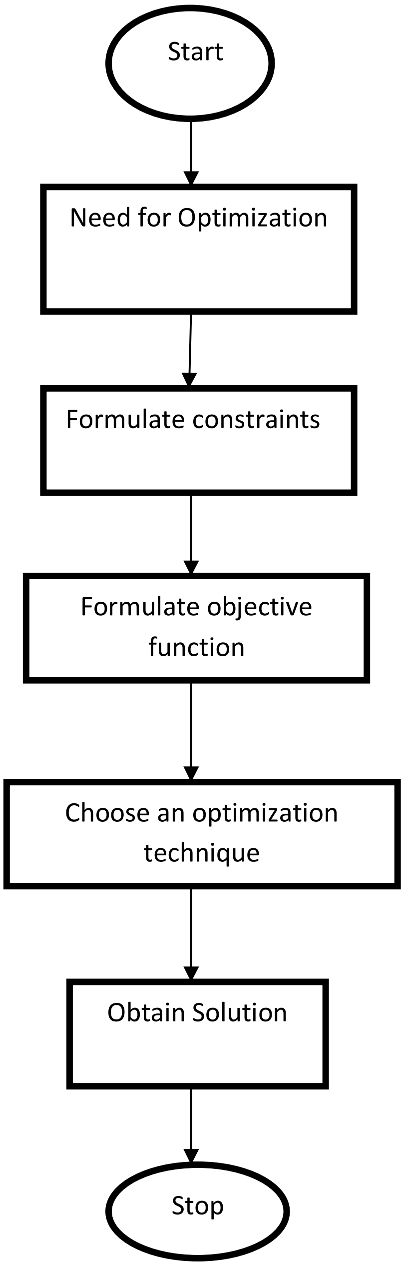

FIG. 5.1: FLOWCHART FOR FORMULATION OF OPTIMIZATION PROBLEM

The Fig. 5.1 shows the flowchart depicting the steps for formulation of an optimization problem. The first step is to realize the need for using optimization in specific design problem. Then the designer needs to choose the important design variables associated with the problem. The formulation of optimization problem involves other considerations such as deciding constraints, objective function and then choosing an efficient optimization technique.

5.3 VARIOUS OPTIMIZATION TECHNIQUES

The various techniques available for the solution of different types of optimization problem are given as follows:

1. **Mathematical Programming Techniques** are useful in finding the minimum of a function of several variables under a prescribed set of constraints. The various types of these techniques are as follows:
    - Calculus Methods
    - Calculus of Variations
    - Non-linear Programming
    - Geometric Programming
    - Quadratic Programming
    - Linear Programming
    - Dynamic Programming
    - Integer Programming
    - Stochastic Programming
    - Separable Programming
    - Multi-objective Programming
    - Network Methods: CPM and PERT
    - Game Theory
    - Simulated Annealing
    - Genetic Algorithms
    - Neural Networks

2. **Stochastic Process Techniques** can be used to analyze problems described by a set of random variables having known probability distributions. This technique include the following methods:
    - Statistical Decision Theory
    - Markov Processes
    - Renewal Theory
    - Simulation Methods
    - Reliability Theory
3. **Statistical Methods** enables us to analyze the experimental data and build empirical models to obtain the most accurate representations of the physical situations. The various types of these techniques are as follows:
    - Regression Analysis
    - Cluster Analysis
    - Pattern Recognition
    - Design of Experiments
    - Discriminate Analysis

The classical methods of differential calculus can be used to find the unconstrained maxima and minima of a function of several variables. These methods assume that the function is differentiable twice with respect to design variables and the derivatives are continuous.

For problems with equality constraints, the Lagrange Multiplier Method can be used. If the problem has inequality constraints, the Kuhn – Tucker conditions can be used to identify the optimum point.

The techniques of non-linear, linear, geometric, quadratic or integer programming can be used for the solution of the particular class of problems indicated by name of the technique. Non-linear programming is the most general method of optimization that can be used to solve any optimization problem. The dynamic programming technique is also a numerical procedure that is useful primarily for the solution of optimal control problems. Stochastic programming deals with the solution of optimization problems in which some of the variables are described by probability distributions.

The above optimization techniques reveal the fact that the techniques for engineering optimization problems could differ from problem to problem. Certain problem involve linear terms for constraints and objective function but certain other problems involve non-linear terms for them etc, unfortunately, there does not exist a single optimization technique which will work for all optimization problems equally efficiently. Some techniques perform better than one problem, but many perform poorly then other problems.

That is why we have a large number of optimization techniques, each technique to solve a particular type of problem. The choice of suitable technique for an optimization problem is, to a large extent, dependent on the user's experience in solving similar problems.

5.4 NEURAL NETWORKS

Artificial neural networks are the results of academic investigations that use mathematical formulations to model nervous system operations. The resulting techniques are being successfully applied in a variety of everyday business applications.

Neural networks (NNs) represent meaningfully different approaches to using computers in the workplace. A neural network is used to learn patterns and relationships in data. The data may be the results of a market research effort, a production process given varying operational conditions, or the experimental data of a process. Regardless of the specifics involved, applying a neural network is substantially different from traditional approaches.

Traditionally a programmer or an analyst specifically codes for every facet of the problem for the computer to understand the situation. Neural networks do not require explicit coding of the problems. For example, to generate a model that performs a sales forecast, a neural network needs to be given only raw data related to problem. The raw data might consist of history of past sales, prices, competitor's prices and other economic variables. The neural network sorts through this information and produces an understanding of the factors impacting sales. The model can then be called upon to provide a prediction of future sales given a forecast of the key factors.

5.4.1 CAPABILITIES OF NEURAL NETWORKS

In principle, NNs can compute any computable function, i.e. they can do everything a normal digital computer can do. Especially anything that can be represented as a mapping between vector spaces can be approximated to arbitrary precision by feed-forward NNs which are the most often used type.

In practice, NNs are especially useful for mapping problems, which are tolerant of some errors, have lots of example data available, but to which hard and fast rules cannot easily be applied. However, NNs are, as of now, difficult to apply successfully to problems that concern manipulation of symbols and memory.

Neural networks are suitable models for qualitative techniques to be applied. We explore how qualitative reasoning could deal with the well known back-propagation learning algorithm. Qualitative models are based on the discritization of their parameters and the use of closed operators on the sets induced by the discritization. Henceforth, a qualitative version of back-propagation is an algorithm in which the variables involved in it belong to one among the finite classes defined. It can be very useful either to realize a physical implementation of the algorithm or as a starting point to develop new reinforcement learning algorithms for neural networks.

Artificial neural networks were first conceived as a very simple model of the processing carried out by natural ones. The first artificial neurons were binary and their interconnecting links had +1 or -1 values. Further models included real valued weights and subsequent ones inherited this level of complexity and even increased it adding non-binary activation functions, recurrent links, pulse activated neurons, etc. And it was not done in vain; the first models were only capable of mapping separable Boolean functions and current ones are able, for example, to recognize people faces or control a complex non-linear process.

In spite of this, there have been three remarkable neural network approaches using qualitative reasoning techniques. The first one is concerning the use of qualitative data as input or output of neural networks, the second one is the development of reinforcement learning algorithms, and the third one is the use discretized weights. Neural networks have proven successful on mapping qualitative input data to real valued output data, or vice versa. A well-known application of this kind is the recognition of speech sounds using as input articulatory features of letters, which is done in.

There have been different attempts to discretized weights for digital implementations, allowing binary and ternary values {+1, -1, 0} for the weights. At the same time many efforts have been put in developing learning algorithms for discrete weights.

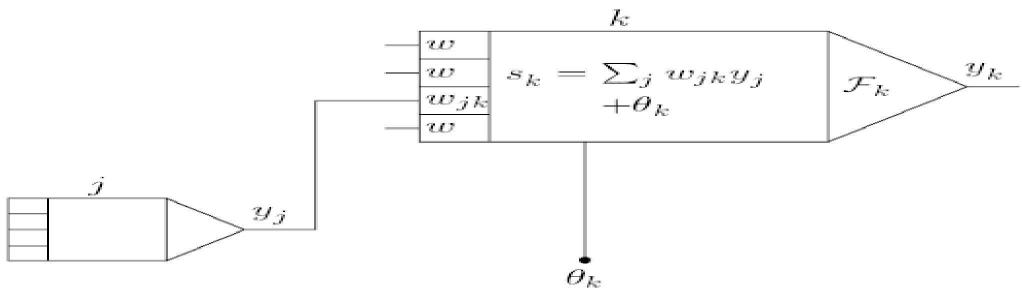

FIG. 5.2: THE BASIC COMPONENTS OF ARTIFICIAL NEURAL NETWORK.

where j, k=different units or signals

s_k=effective input of a unit from its external inputs

w_{jk}=weight which determines the effect which the signal of unit j has on k

y_j =signal corresponding to unit j

Θ_k =an external input for each unit

F_k=an activation function which determines the new level of activation based on the effective input $s_k(t)$ and the current activation $y_k(t)$.

On the other hand, it seems feasible and justifiable to study the learning algorithms used to configure neural networks from a qualitative point of view. It seems feasible because some attempts have already been taken (as discussed previously) and justifiable because it might lead to faster or easier to implement schemes. Take, for instance, gradient algorithms, they intend to follow the steepest gradient descent to reach a global optimum. The main objective of an algorithm of this kind is to compute the direction (positive or negative) a weight must follow to minimize the difference between the output and the desired output. Some of these algorithms (back-propagation, for example) do not even try to find the size of the increment but they just add the weight a quantity proportional to the gradient. One can then say that, to some extent, back-propagation follows a qualitative scheme and we will try to prove it throughout this article.

After this brief introduction the outline of the article is as follows: the next section describes schematically the back-propagation learning algorithm for multilayer perception networks. This algorithm is probably the most popular among neural networks practitioners, and it is proved to obtain very good results on many different applications. After the study of back-propagation various proposals of qualitative versions are given in the following section. Next is an experimental validation of the different back-propagation qualitative algorithms. Finally, we conclude and sketch our future lines of work.

5.4.2 THE BACK-PROPAGATION ALGORITHM

Back-propagation is a learning algorithm for multilayer feed forward neural networks (MFNN) and it is based on gradient descent on the hyper surface of errors. An MFNN is a neural network where neurons are arranged in layers of processing elements (neurons). Two layers are always present: the output and the input layers, and between them there is usually at least one hidden layer. The word feed forward means that activation always flows from the input to the output, i.e. there are no recurrent connections. Fig. 5.3 shows an example of an MFNN.

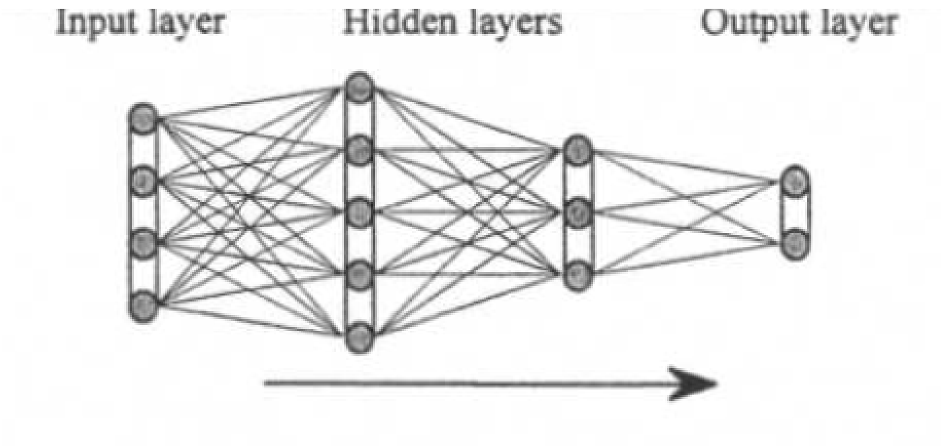

FIG 5.3: MULTILAYER FEED FORWARD NEURAL NETWORKS

Back-propagation, the name of the algorithm, comes from the way derivatives of the errors are calculated: they are first obtained for output neurons and propagated backward through previous layers. The most remarkable characteristic of back-propagation is that it can only obtain the direction in which a weight must be altered to decrease the errors made by the network. This means that after processing the derivatives of the errors respect to all weights, the only true information is their sign. The amount of weight increment results from the heuristic that when error decreases are steep, the step size must be big, and vice versa.

5.5 FUZZY INFERENCE SYSTEM (FIS)

By contrast, a fuzzy inference system employing fuzzy if-then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. This fuzzy modeling or fuzzy identification, first explored systematically by Takagi and Sugeno has found numerous practical applications in control prediction and inference. However, there are some basic aspects of this approach which are in need of better understanding.

More specifically:

1) No standard methods exist for transforming human knowledge or experience into the rule base and database of a fuzzy inference system.

2) There is a need for effective methods for tuning the membership functions (MF's) so as to minimize the output error measure or maximize performance index.

Fuzzy inference systems are also known as fuzzy-rule-based systems, fuzzy models, fuzzy associative memories (FAM), or fuzzy controllers when used as controllers. Basically a fuzzy inference system is composed of five functional blocks as shown in Fig. 5.4.

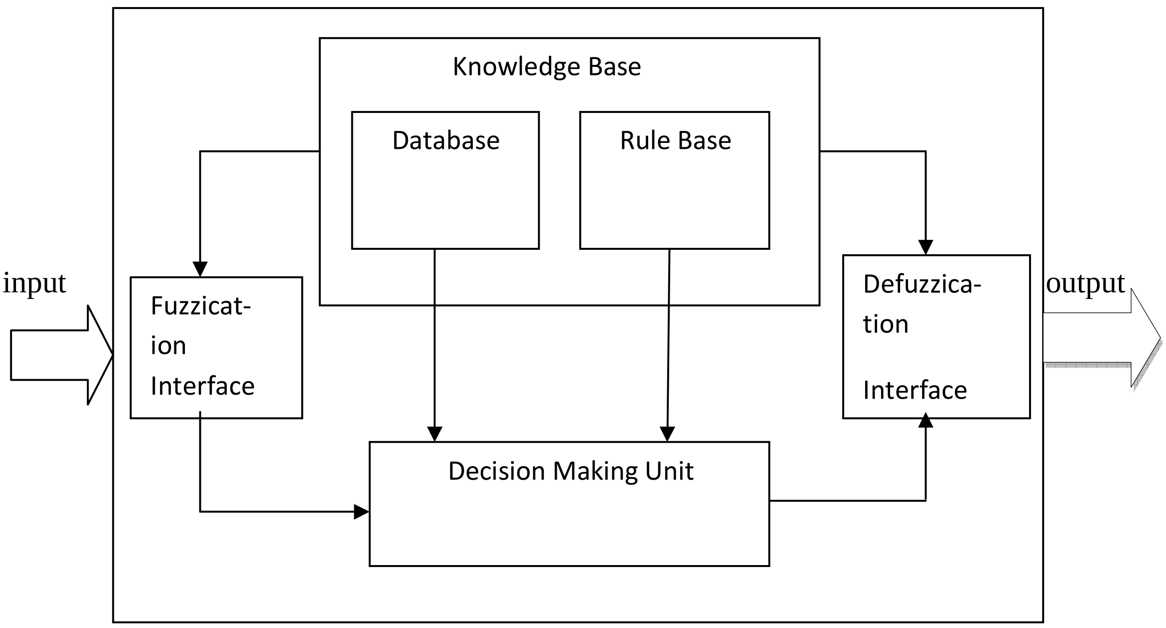

FIG. 5.4: FUZZY INFERENCE SYSTEM

- A rule base containing a number of fuzzy if-then rules.
- A database which defines the membership functions of the fuzzy sets used in the fuzzy rules.
- A decision-making unit which performs the inference operations on the rules.
- A fuzzification interface which transforms the crisp inputs into degrees of match with linguistic values.
- A defuzzification interface which transform the fuzzy results of the inference into crisp output.

Therefore, it seems natural to consider building an integrated system combining the concepts of FIS and ANN modeling. A common way to apply a learning algorithm to a fuzzy system is to represent it in a special neural network like architecture. However the conventional neural network learning algorithms (gradient descent) cannot be applied directly to such a system as the functions used in the inference process are usually non- differentiable. This problem can be tackled by using differentiable functions in the inference system or by not using the standard neural learning algorithm.

In sections 5.5.1 and 5.5.2 we will discuss how to model integrated neuro-fuzzy systems implementing Mamdani and Takagi-Sugeno FIS.

5.5.1 MAMDANI INTEGRATED NEURO-FUZZY SYSTEMS

A Mamdani neuro-fuzzy system uses a supervised learning technique (back-propagation learning) to learn the parameters of the membership functions. Architecture of Mamdani neuro-fuzzy system is illustrated in Fig. 5.5. The detailed function of each layer is as follows:

Layer-1(input layer): No computation is done in this layer. Each node in this layer, which corresponds to one input variable, only transmits input values to the next layer directly. The link weight in layer 1 is unity.

Layer-2 (fuzzification layer): Each node in this layer corresponds to one linguistic label (excellent, good, etc.) to one of the input variables in layer 1. In other words, the output link represents the membership value, which specifies the degree to which an input value belongs to a fuzzy set, is calculated in layer 2. A clustering algorithm will decide the initial number and type of membership functions to be allocated to each of the input variable. The final shapes of the MFs will be fine tuned during network learning.

Layer-3 (rule antecedent layer): A node in this layer represents the antecedent part of a rule. Usually a T-norm operator is used in this node. The output of a layer 3 node represents the firing strength of the corresponding fuzzy rule.

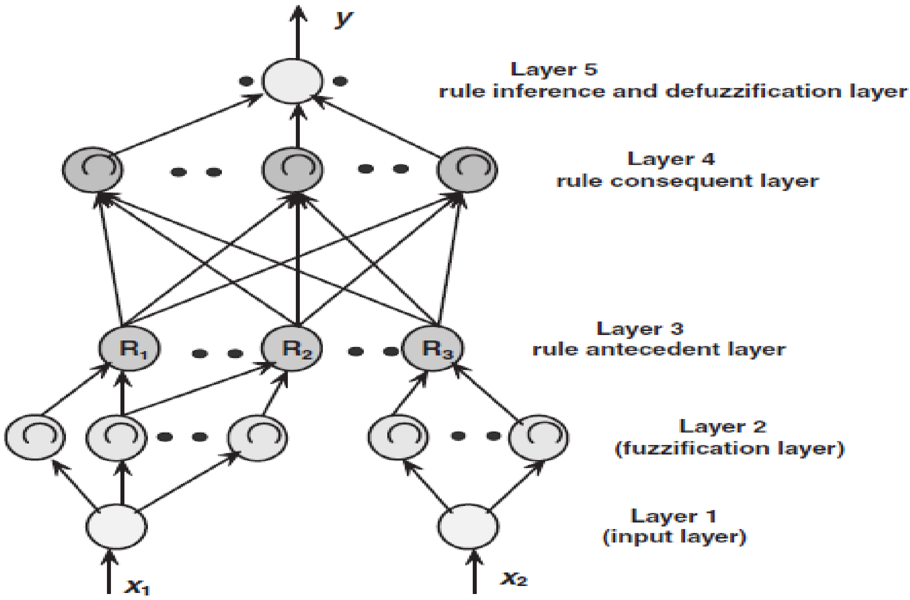

FIG 5.5: MAMDANI NEURO-FUZZY SYSTEM

Layer-4 (rule consequent layer): This node basically has two tasks. To combine the incoming rule antecedents and determine the degree to which they belong to the output linguistic label (high, medium, low, etc.). The number of nodes in this layer will be equal to the number of rules.

Layer-5 (combination and defuzzification layer): This node does the combination of all the rules consequents using a T-conorm operator and finally computes the crisp output after defuzzification.

5.5.2 TAKAGI-SUGENO INTEGRATED NEURO-FUZZY SYSTEM

Takagi-Sugeno neuro-fuzzy systems make use of a mixture of back-propagation to learn the membership functions and least mean square estimation to determine the coefficients of the linear combinations in the rule's conclusions. A step in the learning procedure got two parts: In the first part the input patterns are propagated, and the optimal conclusion parameters are estimated by an iterative least mean square procedure, while the antecedent parameters (membership functions) are assumed to be fixed for the current cycle through the training set. In the second part the patterns are propagated again, and in this epoch, back-propagation is used to modify the antecedent parameters, while the conclusion parameters remain fixed. This procedure is then iterated. The detailed functioning of each layer (as depicted in Fig. 5.6) is as follows: Layers 1, 2 and 3 function the same way as Mamdani FIS.

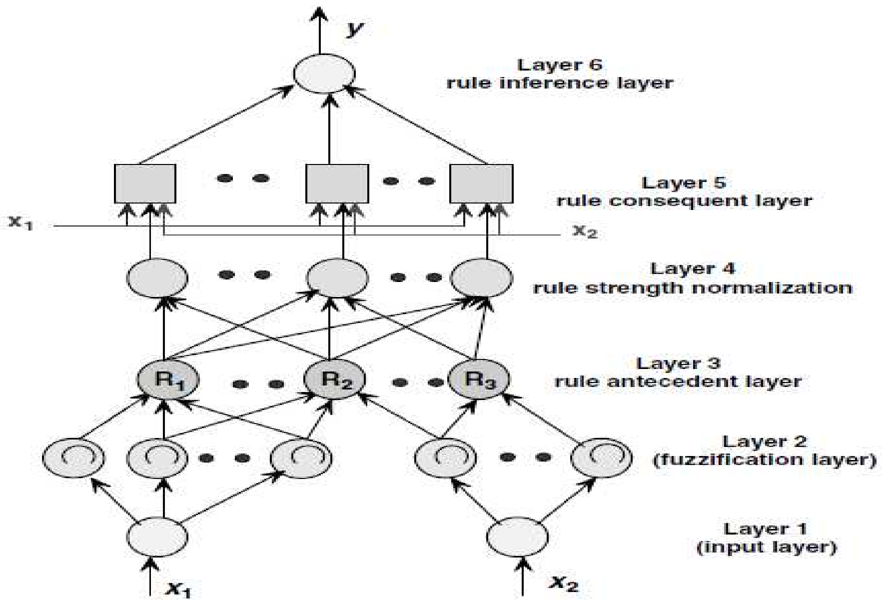

FIG 5.6: TAKAGI-SUGENO NEURO-FUZZY SYSTEMS

Layer 4 (rule strength normalization): Every node in this layer calculates the ratio of the i^{th} rule's firing strength to the sum of all rules firing strength.

$$\overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2,3, \ldots \ldots$$

Layer-5 (rule consequent layer): Every node i in this layer is with a node function

$$\overline{w_i} f_i = \overline{w_i}(p_i x_1 + q_i x_2 + r_i)$$

where w_i is the output of layer 4, and $\{p_i, q_i, r_i\}$ is the parameter set. A well established way is to determine the consequent parameters using the least means squares algorithm.

Layer-6 (rule inference layer): The single node in this layer computes the overall output as the summation of all incoming signals.

$$Overall\ output = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

5.6 ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is perhaps the first integrated hybrid neuro-fuzzy model and the architecture is very similar to Fig. 5.6. A modified version of ANFIS as shown in Fig. 5.7 is capable of implementing the Tsukamoto fuzzy inference system as depicted in Fig. 5.8. In the Tsukamoto FIS, the overall output is the weighted average of each rule's output induced by the rule's firing strength (the product or minimum of the degrees of match with the premise part) and output membership functions. The output membership functions used in this scheme must be monotonically non-decreasing. The first hidden layer is for fuzzification of the input variables and T-norm operators are deployed in the second hidden layer to compute the rule antecedent part. The third hidden layer normalizes the rule strengths followed by the fourth hidden layer where the consequent parameters of the rule are determined. Output layer computes the overall input as the summation of all incoming signals.

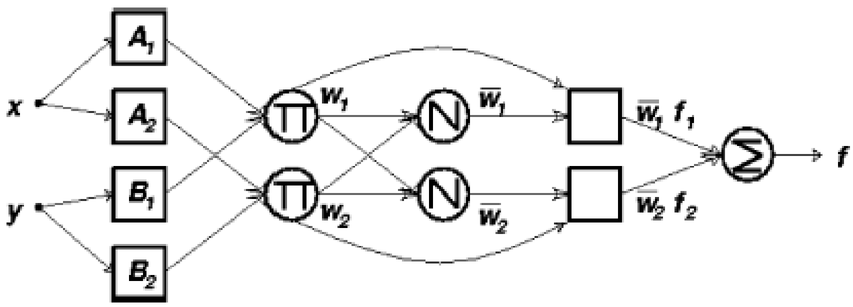

FIG 5.7: ARCHITECTURE OF ANFIS

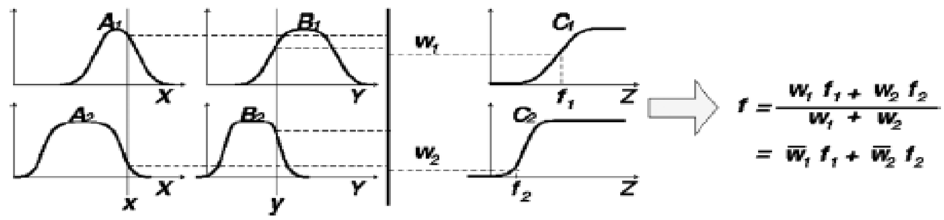

FIG 5.8: TSUKAMOTO FUZZY REASONING

In ANFIS, the adaptation (learning) process is only concerned with parameter level adaptation within fixed structures. For large-scale problems, it will be too complicated to determine the optimal premise-consequent structures, rule numbers etc. The structure of ANFIS ensures that each linguistic term is represented by only one fuzzy set. However, the learning procedure of ANFIS does not provide the means to apply constraints that restrict the kind of modifications applied to the membership functions. When using Gaussian membership functions, operationally ANFIS can be compared with a radial basis function network.

CHAPTER 6 PROBLEM FORMULATION

6.1 INTRODUCTION

In the present study, the gas turbine is regarded as a system consisting of a number of subsystems (components). The operating state is expressed by the parameters that govern such subsystem. The optimization of criteria such as thermal efficiency, specific output and total performance can be treated as a non-linear programming problem. Using the neural networks and back-propagation algorithm even for complicated cycles, the optimum values of parameters can be calculated in a short time.

In this thesis work we will analyze and work for optimization of various gas turbine configurations namely 1/C-having a compressor, turbine and combustor, 1/C/E-having a compressor, regenerator and combustor and turbine, in 1/LP scheme, the high pressure turbine drives the compressor and low pressure turbine gives the network output and in 1/LP/E a heat exchange is added to the cycle to recover heat from the exhaust of low pressure turbine, to decrease the amount of fuel required which increases the thermal efficiency. The criteria for optimization are specific output, thermal efficiency and total performance. The method used for optimization is neural networks and further the part of neural network used is Adaptive Neuro Fuzzy Inference System (ANFIS).

In the present, gas turbine is regarded as a system consisting of a number of subsystems. The optimization of thermal efficiency, specific output and total performance can be formulated as a neural network problem. The design variables are temperature ratios of various components and are assigned certain initial values and then optimized. Constraints, design variables and objective functions for each configuration are different and are described accordingly in subsequent work.

6.2 OPTIMIZATION

Optimization is the art of obtaining best results under the given circumstances. The objective is to maximize desired benefit or minimize the effort required. The optimization methods are also known as mathematical programming techniques. There may be more than one acceptable design and purpose of optimization is to choose best one out of the many acceptable design variables.

Optimization problem is generally stated by specifying the constraints, objective functions and design vector.

6.2.1 DESIGN VARIABLES

An engineering system is described by a set of quantities, which are viewed as variables during the design process. Some quantities are usually fixed at outset and are called pre-assigned parameters. All other quantities are treated as variables in design process and are called design or decision vectors. The design vector is represented as

X_i, where i= 1,2,3,4,.........,n

The design variables are collectively represented as design vector

$$X = \begin{Bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ . \\ . \\ . \\ X_n \end{Bmatrix}$$

In n dimensional design space each point is called design point and represents either a possible or impossible solution to design problem.

6.2.2 CONSTRAINTS

Constraints are basically limitations imposed upon the value of design variables. There may be both equality as well as inequality constraints which may be shown as\

$$g_j\,(X) = 0$$

$or\ g_j(X)\ \geq 0$

$$or\ g_j(X)\ \leq 0$$

Value of the design vector which satisfies

$$g_j\,(X) = 0$$

forms an hyper plane in design surface called constraint surface. The design variables are not chosen arbitrarily. They have to satisfy certain specified functional and other requirements. These restrictions must be satisfied in order to produce an acceptable design called design constraints. The constraints which represent limitations on the behavior or performance of system are termed as behaviour or functional constraints. Constraints depending upon physical limitations are called side constraints.

6.2.3 OBJECTIVE FUNCTION

The criterion with respect to which design is optimized when expressed as function of design variables is known as objective function. Objective function depends upon nature of the problem. If any of the functions among objective and constraint functions are non-linear, the problem is called a non-linear programming problem.

6.2 STATEMENT OF STANDARD OPTIMIZATION PROBLEM

Optimization problem can be stated as follows:

$$X = \begin{Bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ . \\ . \\ . \\ X_n \end{Bmatrix}$$

which minimizes F(X) subject to constraints

$$g_j(X) \le 0 \quad j = 1,2, \dots \dots .., m$$

where X is design vector of n dimensions, F(X) is called the objective function, $g_j(X)$ is the inequality constraint.

6.3 FORMULATION OF 1/C CONFIGURATION

There are two design variables in this problem namely X_1 and X_2. The optimization problem for the 1/C can be stated as follows:

Find $X = \begin{Bmatrix} X_1 \\ X_2 \end{Bmatrix} = \begin{Bmatrix} \theta_C \\ \theta_T \end{Bmatrix}$

which minimizes

$$\eta_{\mathrm{th}} = -\{\eta_B[1 - \frac{(\theta\theta_T - 1)}{(\theta - \theta_C)}]\}$$

$$\mathrm{I} = -[\theta(1 - \theta_T) - (\theta_C - 1)]$$

subject to constraints

$$\theta_C-1\geq 0$$

$$\eta_{th}\geq 0$$

$$\theta_T\ \theta-1\geq 0$$

6.4 FORMULATION OF 1/C/E CONFIGURATION

There are three design variables in this problem namely X_1, X_2 and X_3. The optimization problem for the 1/C/E can be stated as follows:

Find $X = \begin{Bmatrix} X_1 \\ X_2 \\ X_3 \end{Bmatrix} = \begin{Bmatrix} \theta_C \\ \theta_E \\ \theta_T \end{Bmatrix}$

which minimizes

$$\eta_{th} = -\eta_B[\frac{\theta(1-\theta_T)-(\theta_C-1)}{\theta-\theta_C\theta_E}]$$

$$\mathrm{I} = -[\theta(1-\theta_T)-(\theta_C-1)]$$

subject to constraints

$$\theta_C-1\geq 0$$

$$1\leq\theta_E$$

$$\theta-\theta_C\theta_E\geq 0$$

$$0\leq\theta_T\leq 1$$

6.5 FORMULATION OF 1/LP CONFIGURATION

There are three design variables in this problem namely X_1, X_2 and X_3. The optimization problem for the 1/LP can be stated as follows:

Find $X = \begin{Bmatrix} X_1 \\ X_2 \\ X_3 \end{Bmatrix} = \begin{Bmatrix} \theta_C \\ \theta_{HT} \\ \theta_{LT} \end{Bmatrix}$

which minimizes

$$\eta_{th} = -\eta_B \frac{\theta\theta_{HT}(1-\theta_{LT})}{\theta - \theta_C}$$

$$I = -[\theta\ \theta_{HT}(1-\theta_{LT})]$$

subject to constraints

$$\theta \geq \theta_C \geq 1$$

$$0 \leq \theta_{HT} \leq 1$$

$$0 \leq \theta_{LT} \leq 1$$

6.6 FORMULATION OF 1/LP/E CONFIGURATION

There are four design variables in this problem namely X_1, X_2, X_3 and X_4. The optimization problem for the 1/LP/E can be stated as follows:

Find $X = \begin{Bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \end{Bmatrix} = \begin{Bmatrix} \theta_C \\ \theta_E \\ \theta_{HT} \\ \theta_{LT} \end{Bmatrix}$

which minimizes

$$\eta_{th} = -[\eta_B \frac{\theta\theta_{HT}(1-\theta_{LT})}{\theta - \theta_C\theta_E}]$$

$$I = -[\theta\ \theta_{HT}(1-\theta_{LT})]$$

subject to constraints

$$\theta_C \geq 1$$

$$\theta_E \geq 1$$

$$\theta \geq \theta_E$$

$$0 \leq \theta_{HT} \leq 1$$

$$0 \leq \theta_{LT} \leq 1$$

The results have been obtained by optimization for four different configurations 1/C, 1/C/E, 1/LP and 1/LP/E using Adaptive Neuro Fuzzy Inference System (ANFIS). In this technique Matlab Software had been used, in which further ANFIS had been used. The data assumed is given in beginning. In the explanation of the present work the results are validated with results of the research paper published by Y. Tsujikawa et al. [7]. In their research work they had used Multiplier Method for their optimization.

7.1 RESULTS FOR 1/C CONFIGURATION

The results for the 1/C configuration is shown in Fig. 7.1(a) and Fig. 7.1(b) in which the results are obtained for the efficiency and specific work done for the two same inputs. In the Fig. 7.1(a) and Fig. 7.1(b) the value of efficiency and specific work done are obtained for $\theta_C =$ 2.837 (cr=compression ratio) and $\theta_T = 0.4546$ (tr=turbine ratio). The output efficiency (effi.=efficiency), $\eta_{th} = 0.407$ and specific work done (swd=specific work done), l = 283 KW/kg sec.

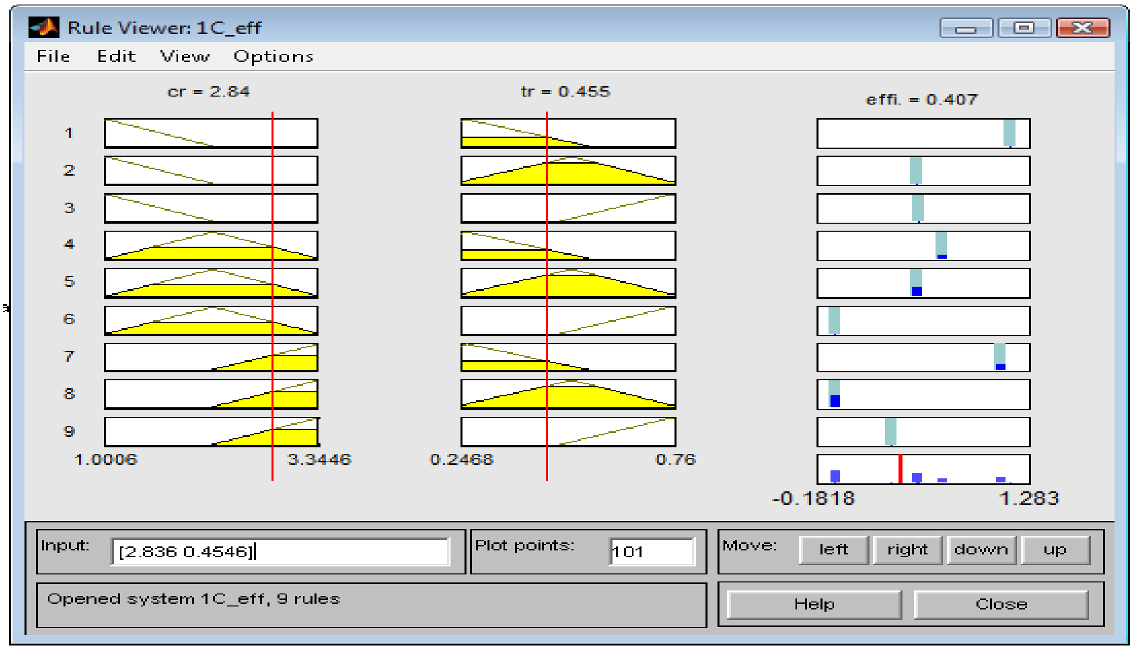

FIG. 7.1(a): RESULT FOR EFFICIENCY FOR 1/C CONFIGURATION

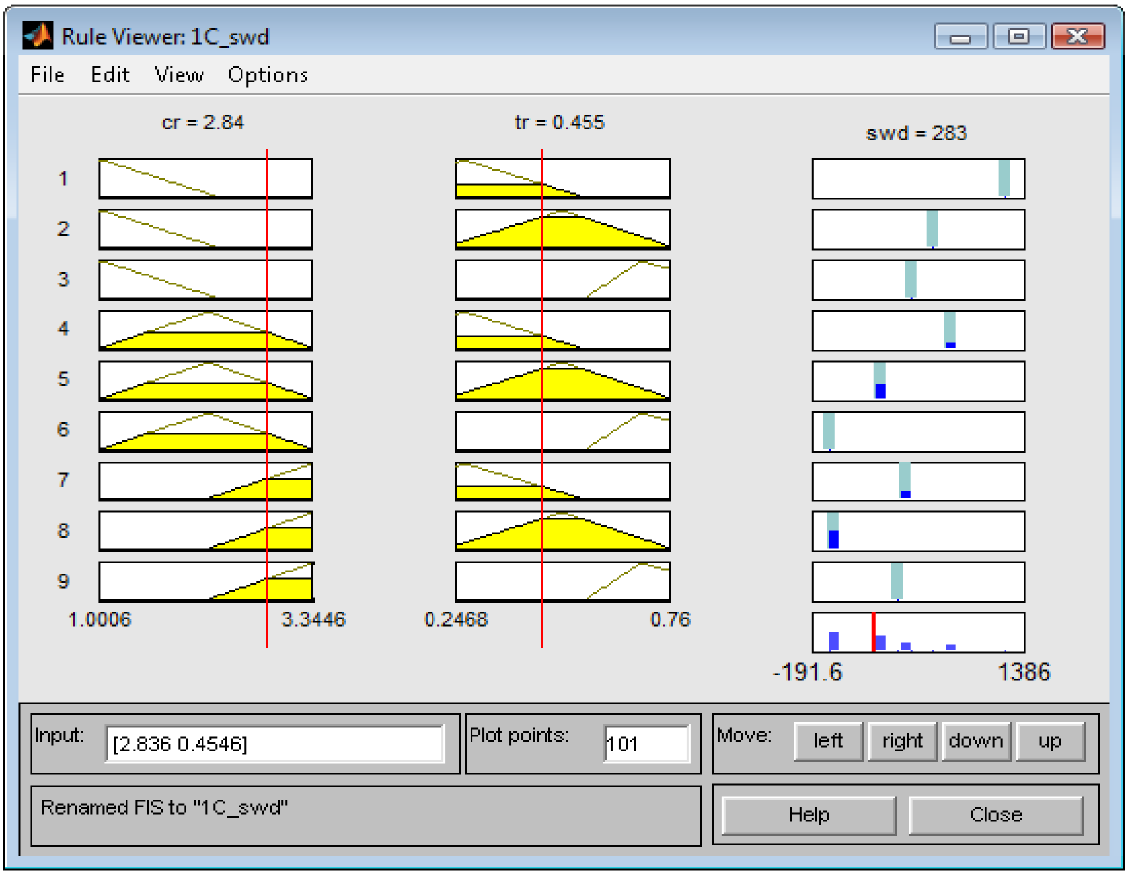

FIG. 7.1(b): RESULT FOR SPECIFIC WORK DONE FOR 1/C CONFIGURATION

The results for other values of θ_C and θ_T and comparison of the results with the results obtained by Multiplier Method are shown in Table 7.1.

Values of Various Parameters		Objective Function			
		ANFIS		Multiplier Method	
θ_c	θ_t	η_{th}	I(KW/kg sec)	η_{th}	I(KW/kg sec)
2.8357	0.4546	40.70%	283	40.36%	287.1
2.1341	0.5623	36.70%	356	36.12%	346.8
2.4012	0.5144	40.50%	319	38.79%	337.1

Table 7.1: Comparison of the Results Obtained with those of Multiplier Method for 1/C Configuration.

From the results obtained, it is seen that the value of temperature ratios that gives maximum specific output is different from that giving maximum thermal efficiency. As there are two inputs and one output so the ANFIS will generate the surface between the three which are shown in Fig. 7.2 and Fig. 7.3 for efficiency and specific work done respectively.

The specific output depends upon the value of θ_C and θ_T. As the value of θ_C and θ_T increases the work required for compression increases and turbine expansion work decreases. So the specific output decreases. A lower value of θ_C and θ_T is desired. However, thermal efficiency increases as the value of θ_C increases because lesser amount of fuel will be required to get same temperature rise, as the temperature of air leaving the compressor will be higher.

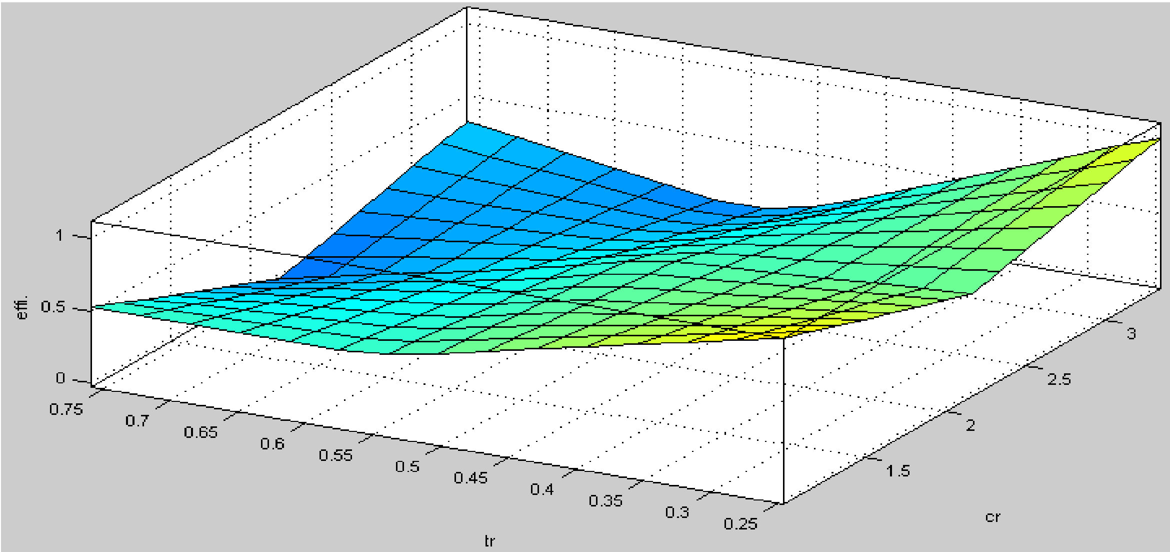

FIG. 7.2: SURFACE FOR 1/C CONFIGURATION FOR EFFICIENCY

It is clear from the Fig. 7.2 and Fig. 7.3 that as the value of θ_C falls, more amount of fuel will be required to get the same temperature rise as the temperature of air coming out of the compressor will be at a lower temperature and the work required for compression will be reduced and hence there will be net increase in specific output. As the value of θ_T increases, temperature of turbine exhaust increases. There will be decrease in the work output, however, the work required for running the compressor will be less and it predominates over the decrease in the work output of the turbine resulting in net increase in the work output.

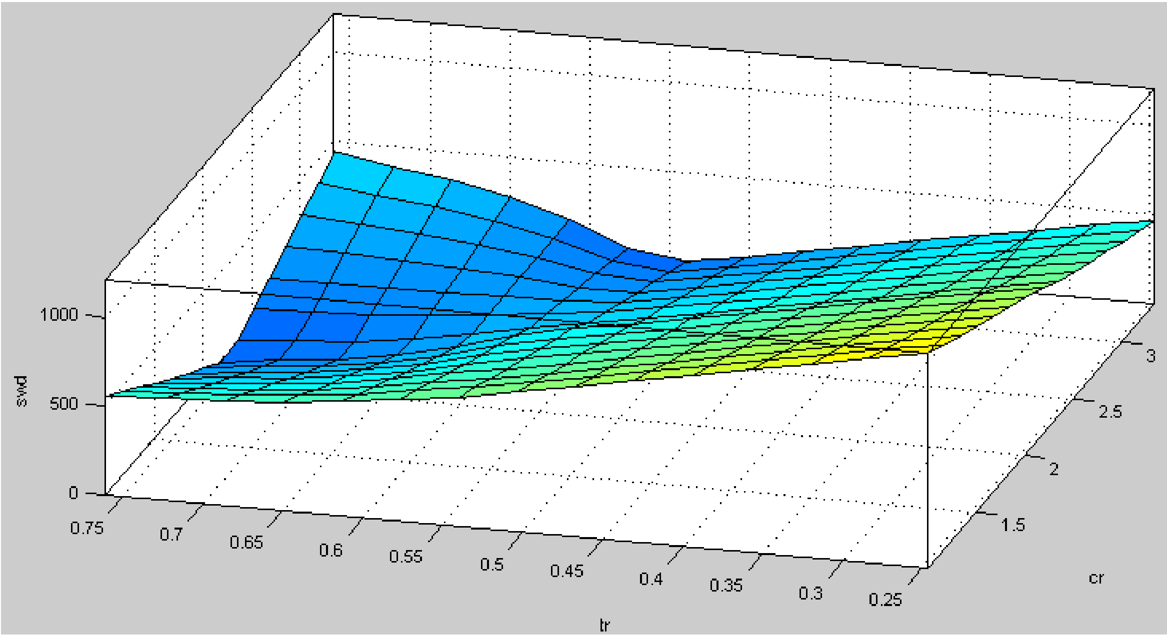

FIG. 7.3: SURFACE FOR 1/C CONFIGURATION FOR SPECIFIC WORK DONE

7.2 RESULTS FOR 1/C/E CONFIGURATION

The results for the 1/C/E configuration is shown in Fig. 7.4(a) and Fig. 7.4(b) in which the results are obtained for the efficiency and specific work done for the two same inputs. In the Fig. 7.4(a) and Fig. 7.4(b) the value of efficiency and specific work done are obtained for $\theta_C = 2.001$ (cr=compression ratio), $\theta_E = 1.363$ (rr=regenerator ratio) and $\theta_T = 0.5962$ (tr=turbine ratio). The output efficiency (effi. =efficiency), $\eta_{th} = 0.427$ and specific work done (swd=specific work done), l = 328 KW/kg sec.

For 1/C/E configuration, the value of specific output falls as value of θ_C and θ_T increases. The value of thermal efficiency increases as the value of θ_C and θ_E increases and there occurs a fall in the value of θ_T. More compressor work is compensated by the increase in the turbine work output and more heat is transferred to the air entering into combustion chamber by the hot gases in the regenerator.

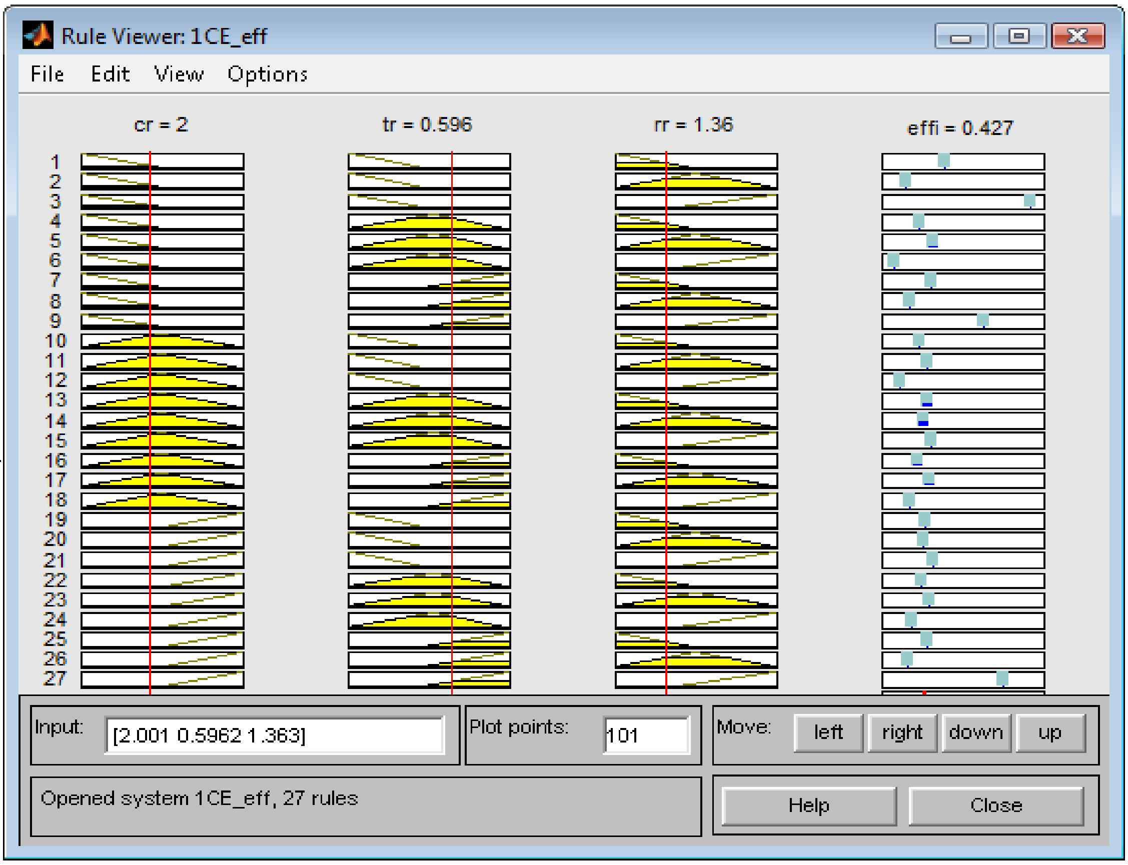

FIG. 7.4(a): RESULT FOR EFFICIENCY FOR 1/C/E CONFIGURATION

The table showing the comparison of the results of the Multiplier Method and the ANFIS are shown in Table 7.2.

Values of Various Parameters			Objective Function			
			ANFIS		Multiplier Method	
θ_C	θ_T	θ_E	η_{th}	I(KW/kg s)	η_{th}	I(KW/kg s)
2.001	0.6393	1.363	42.70%	328	43.79%	324.6
2.152	0.5656	1.236	42.20%	344	42.71%	327.6
1.833	0.5962	1.558	47.80%	341	44.33%	311.4

TABLE 7.2: Comparison of the Results Obtained with those of Multiplier Method for 1/C/E Configuration.

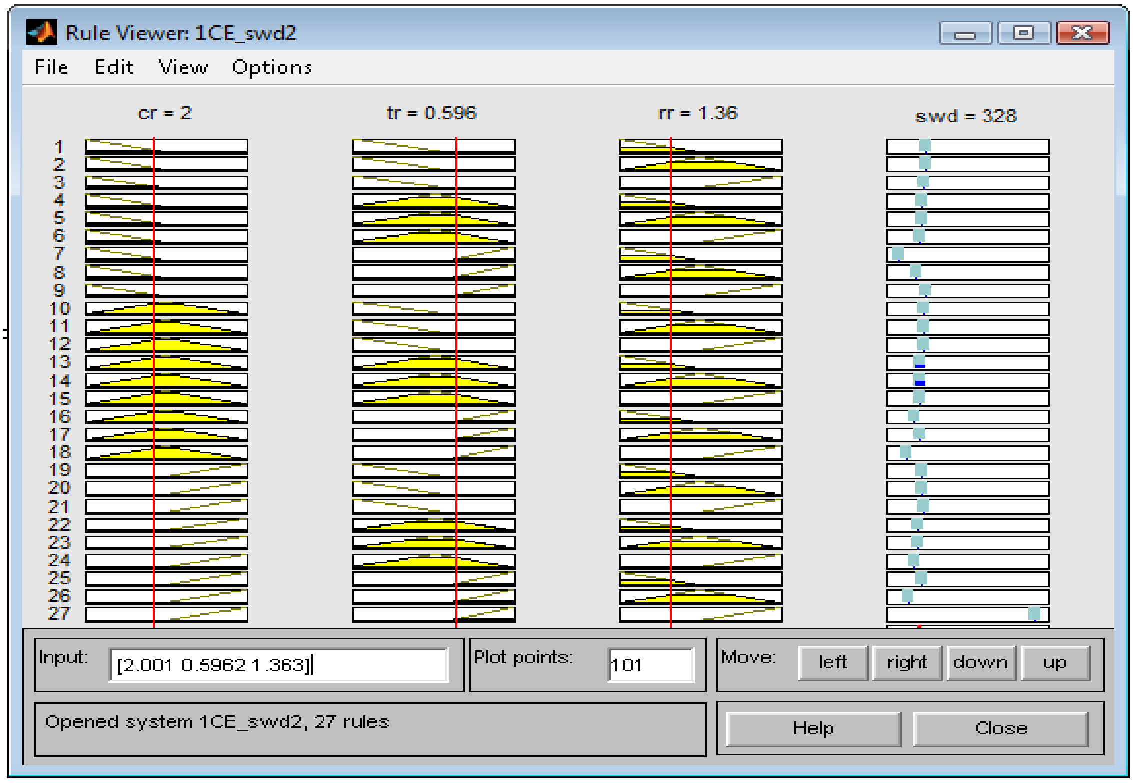

FIG. 7.4(b): RESULT FOR SPECIFIC WORK DONE FOR 1/C/E CONFIGURATION

The surfaces generated by the ANFIS are shown in Fig. 7.5 for efficiency plotted on the cr and tr axis.

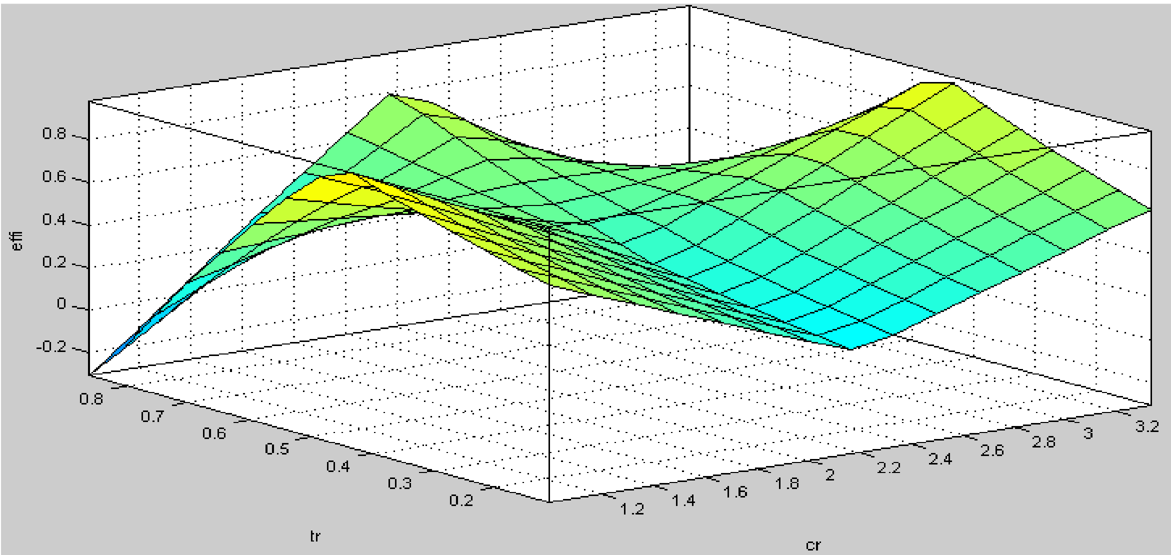

FIG. 7.5: SURFACE FOR 1/C/E CONFIGURATION FOR EFFICIENCY

The surfaces generated by the ANFIS are shown in Fig. 7.6 for specific work done plotted on cr and rr axis.

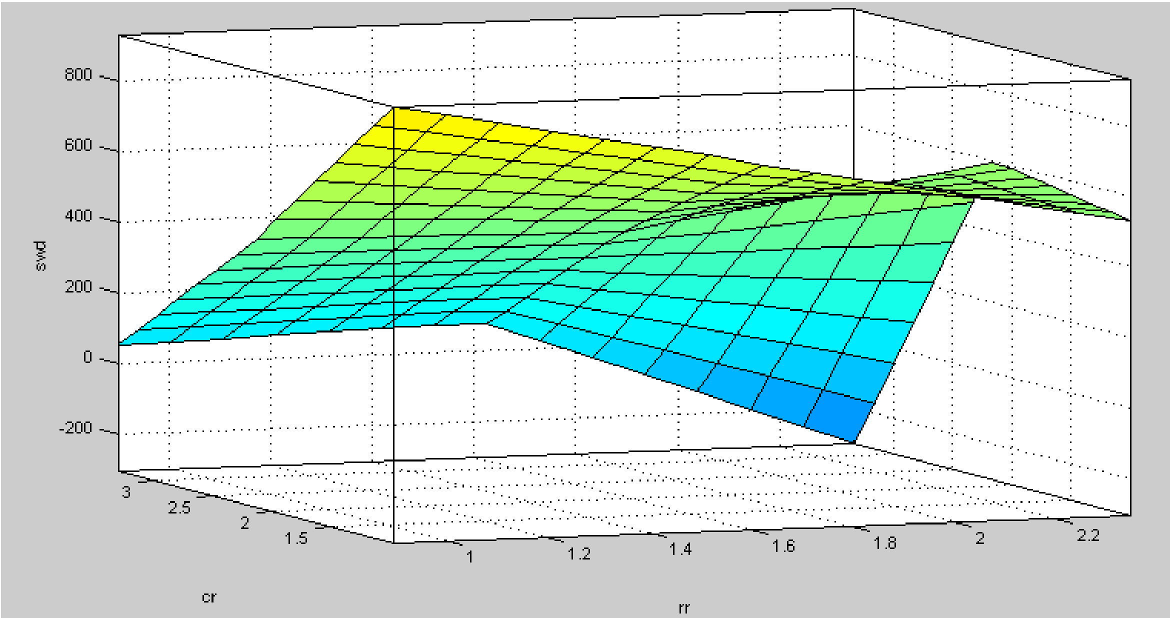

FIG. 7.6: SURFACE FOR 1/C/E CONFIGURATION FOR SPECIFIC WORK DONE

From the Fig. 7.5 and Fig. 7.6 it is clear that the specific work output increases as θ_T falls because much more work will be obtained from the turbine. However, work input required for the compressor also increases; however, the former predominates over the latter, resulting in increasing the work output. The thermal efficiency falls due to increased value of work input to the compressor, less heat is transferred to the air going to the combustion chamber from regenerator as indicated by fall in the value of θ_E and lower value of turbine exhaust temperature resulting in more fuel consumption.

7.3 RESULTS FOR 1/LP CONFIGURATION

The results for the 1/LP configuration is shown in Fig. 7.7(a) and Fig. 7.7(b) in which the results are obtained for the efficiency and specific work done for the two same inputs. In the Fig. 7.7(a) and Fig. 7.7(b) the value of efficiency and specific work done are obtained for $\theta_C =$ 3.028 (cr=compression ratio), $\theta_{HT} = 0.6006$ (hpr=high pressure turbine ratio) and $\theta_{LT} =$

0.7054 (lpr=low pressure turbine ratio). The output efficiency (effi.=efficiency), η_{th} = 0.449 and specific work done (swd=specific work done), l = 286 KW/kg sec.

For 1/LP configuration, a higher value of θ_{HT} and a lower value of θ_{LT} results in both increased specific work done and thermal efficiency. A higher value of θ_C results in increased thermal efficiency. So the optimum values of the efficiency and specific work done should be higher at the higher values of θ_{HT} and θ_{LT} as they directly proportional. By the induction a second turbine the energy that we loosing gets recovered hence the thermal efficiency gets enhanced. The table showing the comparison of the results of the Multiplier Method and the ANFIS are shown in Table 7.3.

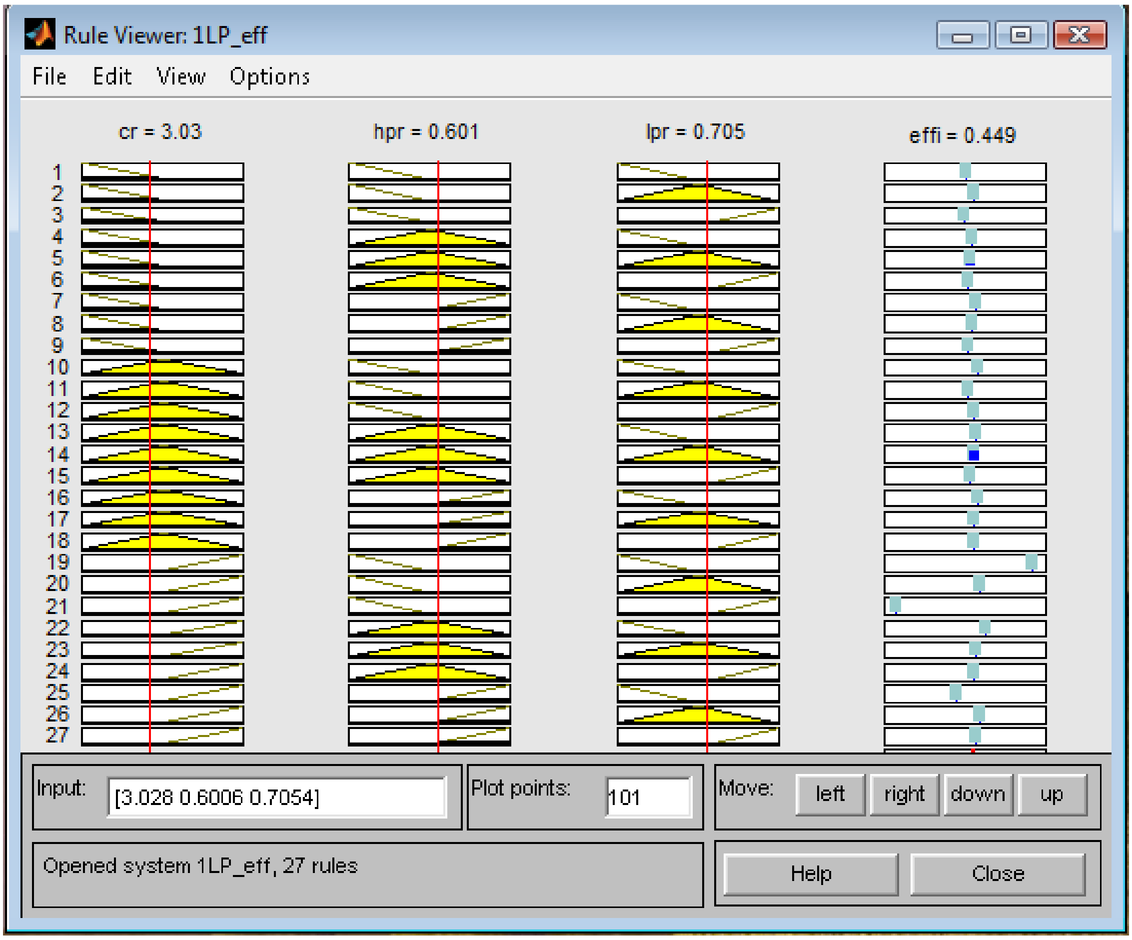

FIG. 7.7(a): RESULT FOR EFFICIENCY FOR 1/LP CONFIGURATION

Values of Various Parameters			Objective Function			
			ANFIS		Multiplier Method	
θ_C	θ_{HT}	θ_{LT}	η_{th}	I(KW/kg s)	η_{th}	I(KW/kg s)
3.028	0.6006	0.7054	44.90%	286	43.97%	288.4
2.187	0.7678	0.715	39.50%	360	38.12%	359
2.497	0.7065	0.6992	40.80%	345	41.59%	347.8

TABLE 7.3: Comparison of the Results Obtained with those of Multiplier Method for 1/LP Configuration.

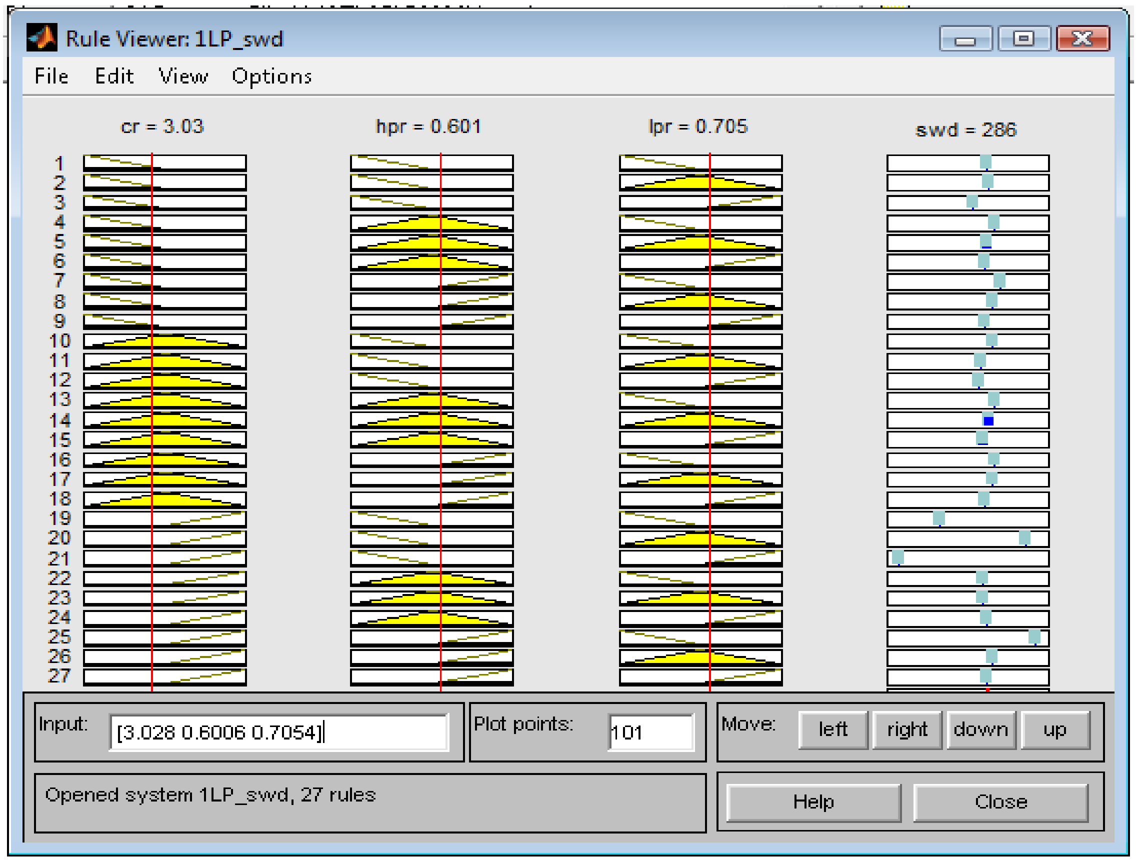

FIG. 7.7(b): RESULT FOR SPECIFIC WORK DONE FOR 1/LP CONFIGURATION

The surfaces generated by the ANFIS are shown in Fig. 7.8(a), Fig. 7.8(b) and Fig. 7.8(c) for efficiency plotted on the different axis for different set of parameters i.e. cr, hpr and lpr. This shows the variation of efficiency with different parameters. In Fig. 7.8(a) the efficiency is plotted against hpr and cr, in Fig. 7.8(b) the efficiency is plotted against lpr and cr, in Fig. 7.8(c) the efficiency is plotted against lpr and hpr.

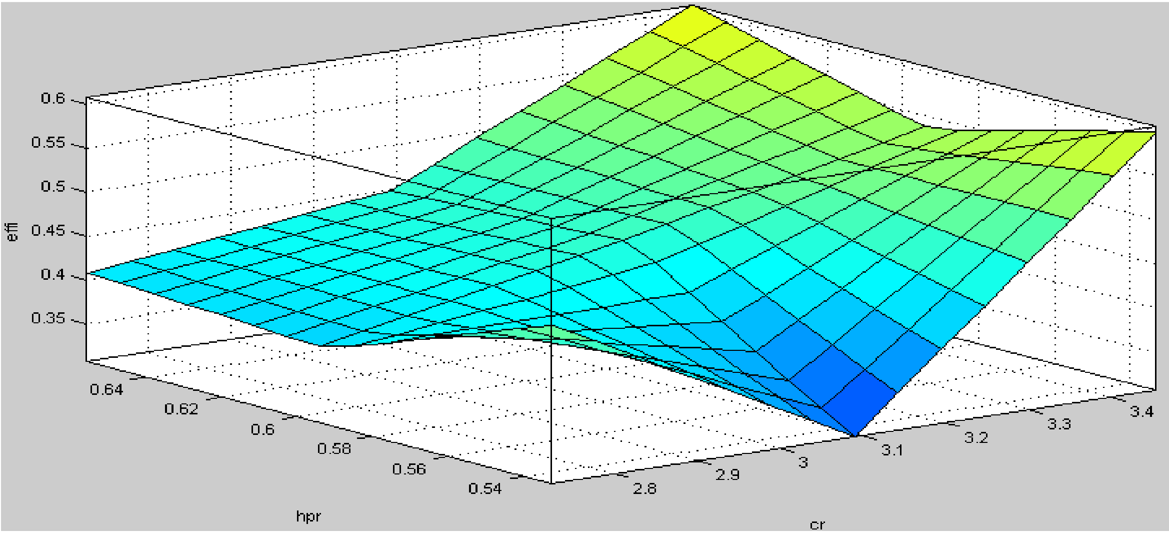

FIG. 7.8(a): SURFACE FOR 1/LP CONFIGURATION FOR EFFICIENCY ON HPR-CR AXIS

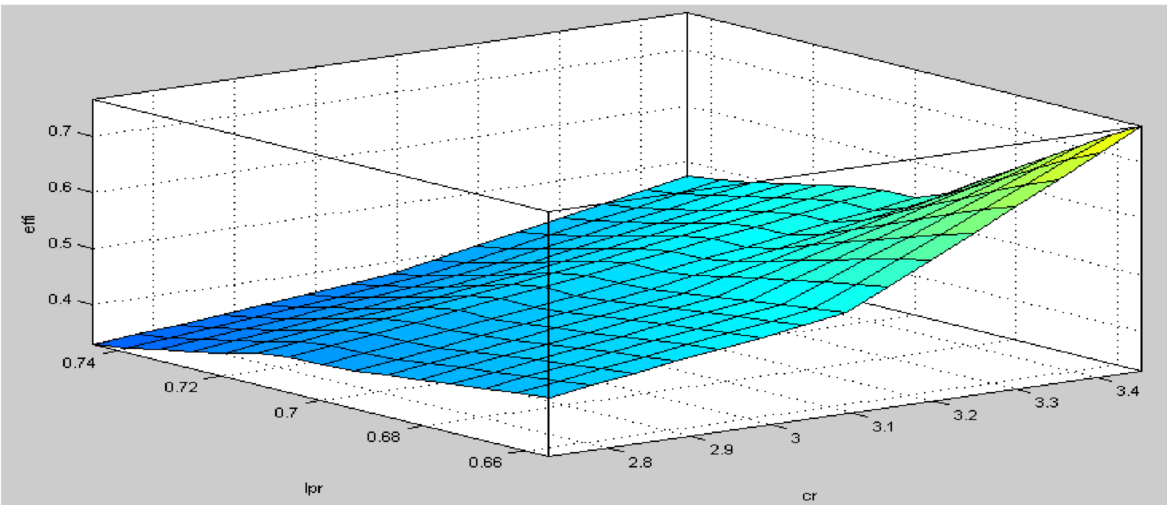

FIG. 7.8(b): SURFACE FOR 1/LP CONFIGURATION FOR EFFICIENCY ON LPR-CR AXIS

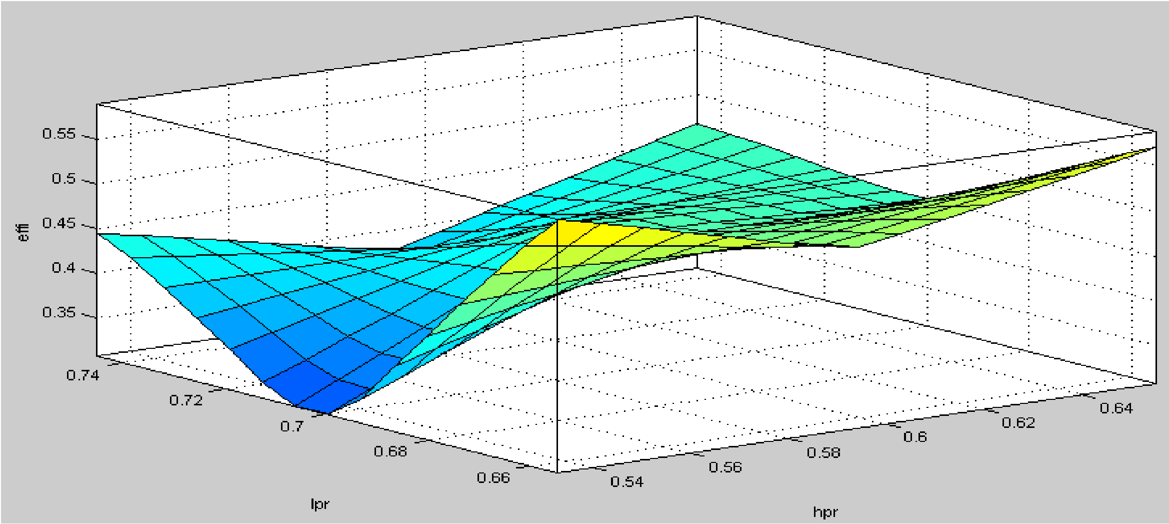

FIG. 7.8(c): SURFACE FOR 1/LP CONFIGURATION FOR EFFICIENCY ON LPR-HPR AXIS

The surfaces generated by the ANFIS are shown in Fig. 7.9(a), Fig. 7.9(b) and Fig. 7.9(c) for specific work done plotted on the different axis for different set of parameters i.e. cr, hpr and lpr. This shows the variation of specific work done with different parameters. In Fig. 7.9(a) the specific work done is plotted against hpr and cr, in Fig. 7.9(b) the specific work done is plotted against lpr and cr, in Fig. 7.9(c) the specific work done is plotted against lpr and hpr.

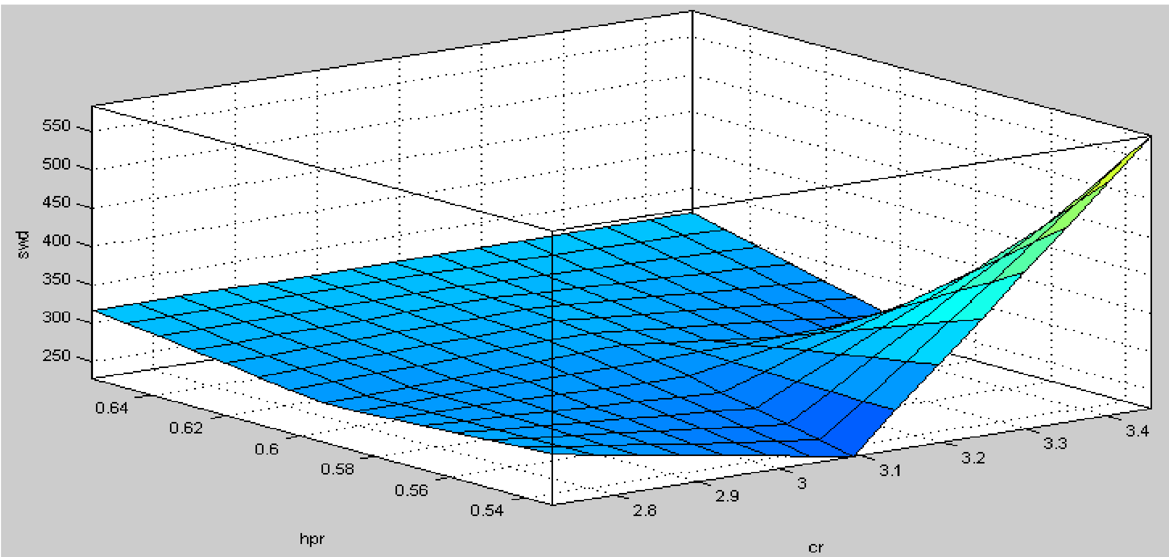

FIG. 7.9(a): SURFACE FOR 1/LP CONFIGURATION FOR SPECIFIC WORK DONE ON HPR-CR AXIS

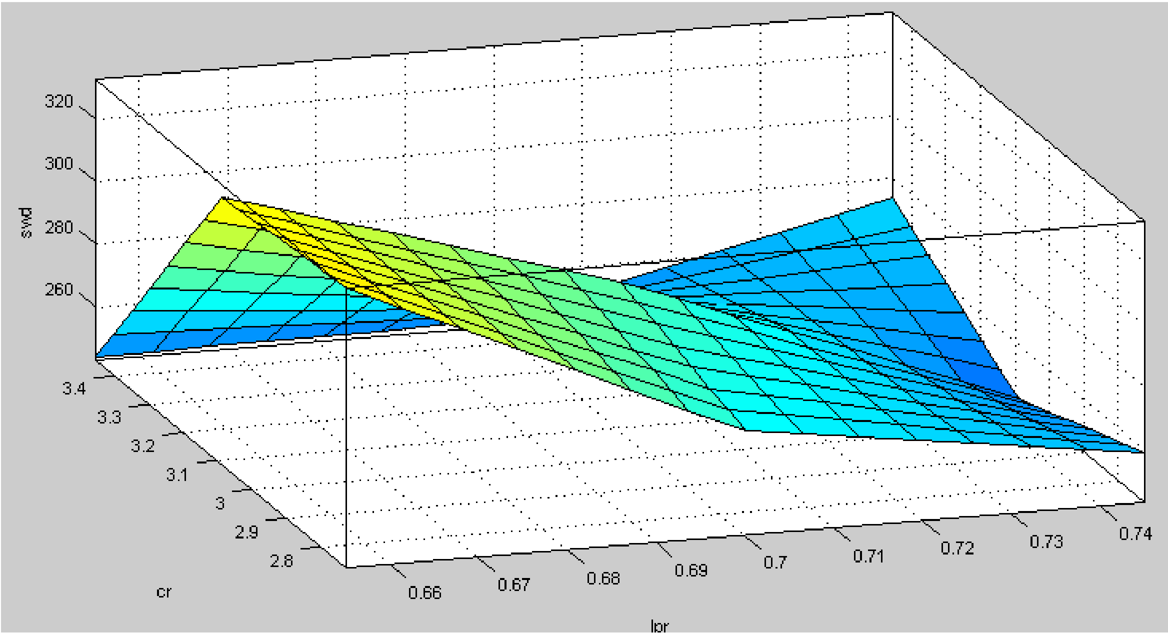

FIG. 7.9(b): SURFACE FOR 1/LP CONFIGURATION FOR SPECIFIC WORK DONE ON LPR-CR AXIS

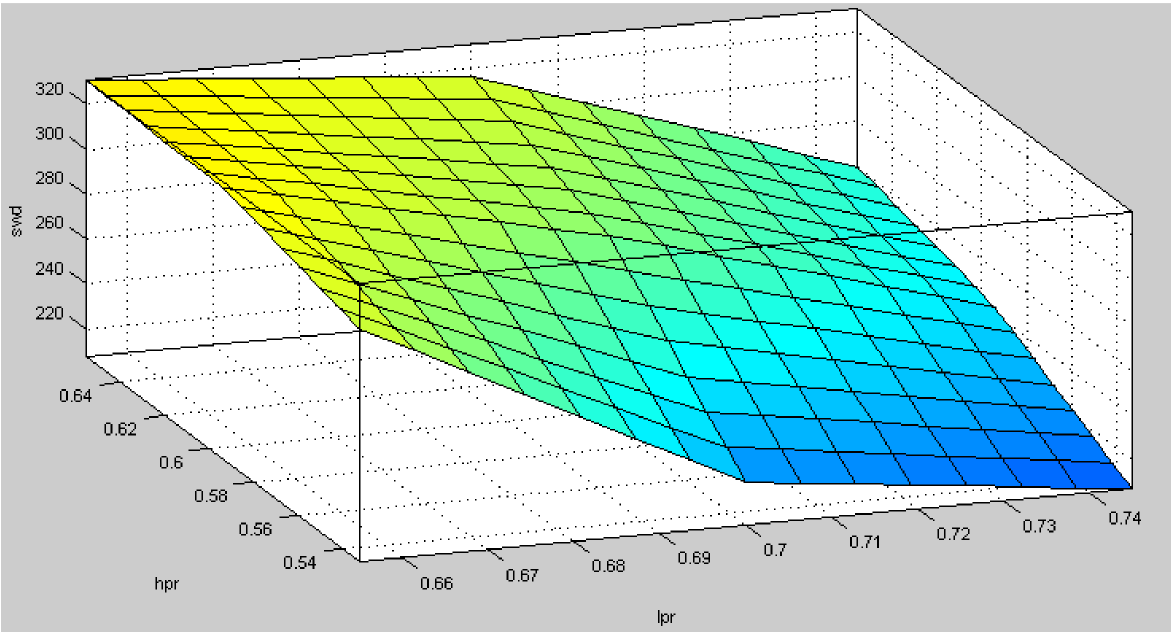

FIG. 7.9(c): SURFACE FOR 1/LP CONFIGURATION FOR SPECIFIC WORK DONE ON LPR-HPR AXIS

7.4 RESULTS FOR 1/LP/E CONFIGURATION

The results for the 1/LP/E configuration is shown in Fig. 7.10(a) and Fig. 7.10(b) in which the results are obtained for the efficiency and specific work done for the two same inputs. In the Fig. 7.10(a) and Fig. 7.10(b) the value of efficiency and specific work done are obtained for $\theta_C = 2.073$ (cr=compression ratio), $\theta_E = 1.300$ (rr=regenerator ratio), $\theta_{HT} = 0.7892$ (hpr=high pressure turbine ratio) and $\theta_{LT} = 0.7353$ (lpr=low pressure turbine ratio). The output efficiency (effi.=efficiency), $\eta_{th} = 0.449$ and specific work done (swd=specific work done), l = 286 KW/kg sec. θ_C

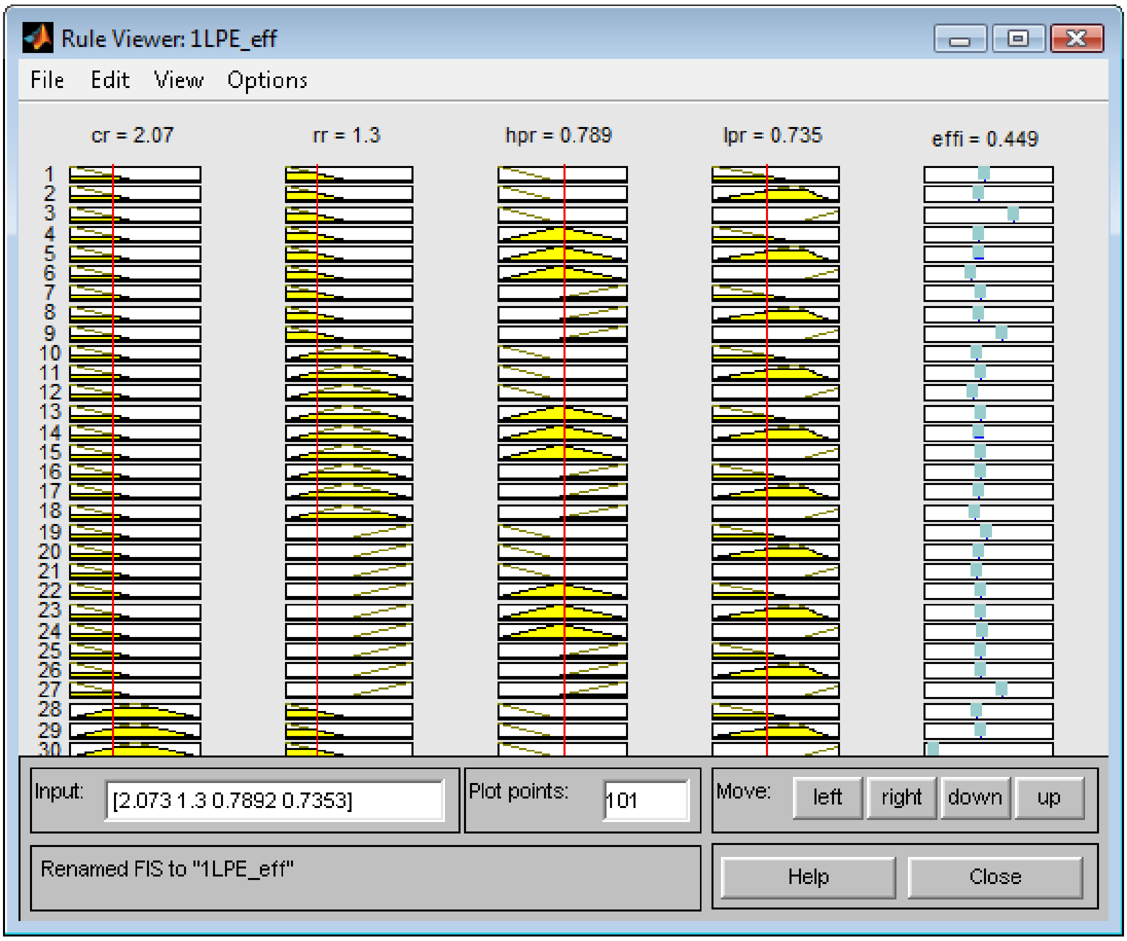

FIG. 7.10(a): RESULT FOR EFFICIENCY FOR 1/LP/E CONFIGURATION

For 1/LP/E configuration, a higher value of θ_{HT} and a lower value of θ_{LT} results in the increased value of both thermal efficiency and specific output. A higher value of θ_C and θ_E also increase the thermal efficiency.

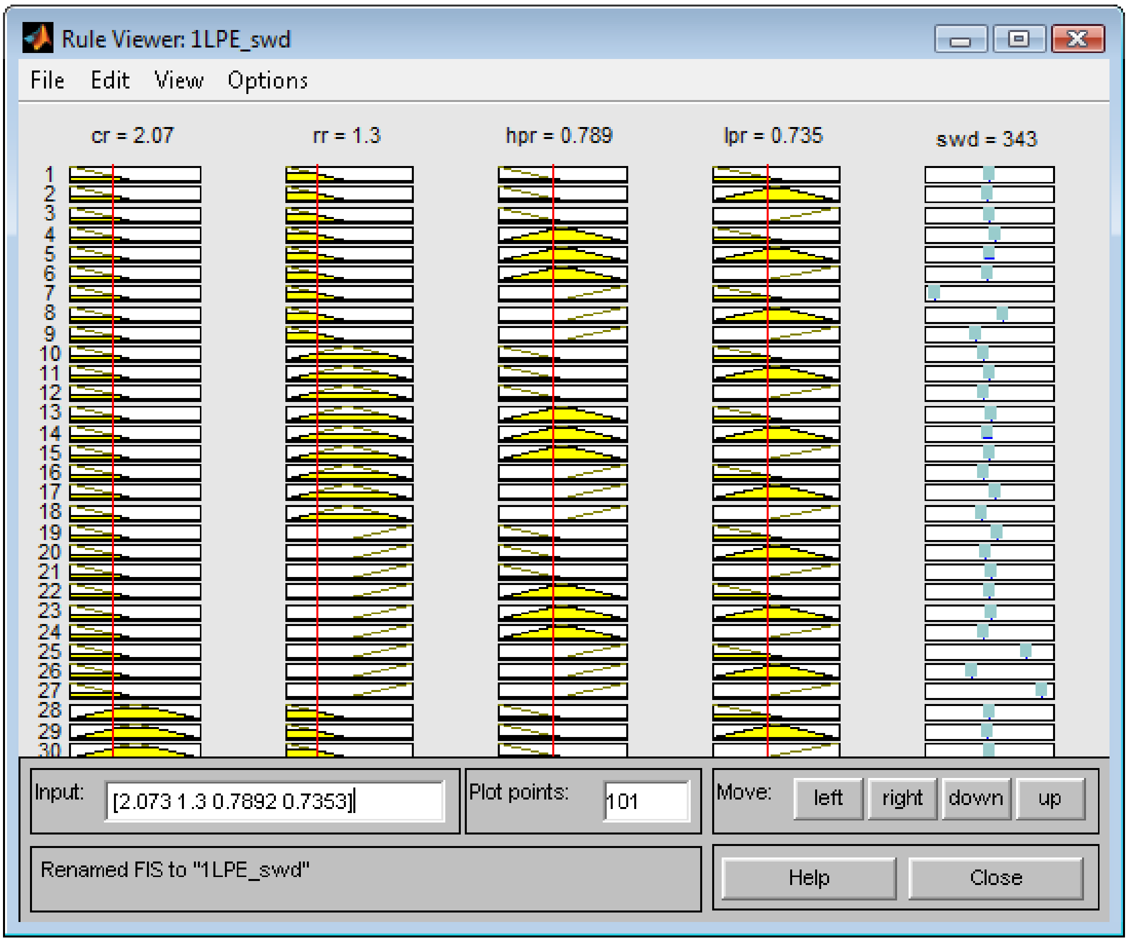

FIG. 7.10(b): RESULT FOR SPECIFIC WORK DONE FOR 1/LP/E CONFIGURATION

The table showing the comparison of the results of the Multiplier Method and the ANFIS are shown in Table 7.4.

Values of Various Parameters				Objective Function			
				ANFIS		Multiplier Method	
θ_C	θ_E	θ_{HT}	θ_{LT}	η_{th}	I(KW/kg s)	η_{th}	I(KW/kg s)
2.073	1.3	0.7892	0.7353	44.90%	343	44.98%	341.5
2.199	1.194	0.7645	0.7242	41.80%	344	43.53%	344.8
1.866	1.517	0.8297	0.76	44.00%	323	44.40%	325.1

TABLE 7.4: Comparison of the Results Obtained with those of Multiplier Method for 1/LP/E Configuration.

The surfaces generated by the ANFIS are shown in Fig. 7.11 for efficiency on the hpr and cr axis and in Fig. 7.12 for specific work done plotted on the lpr and cr axis is shown.

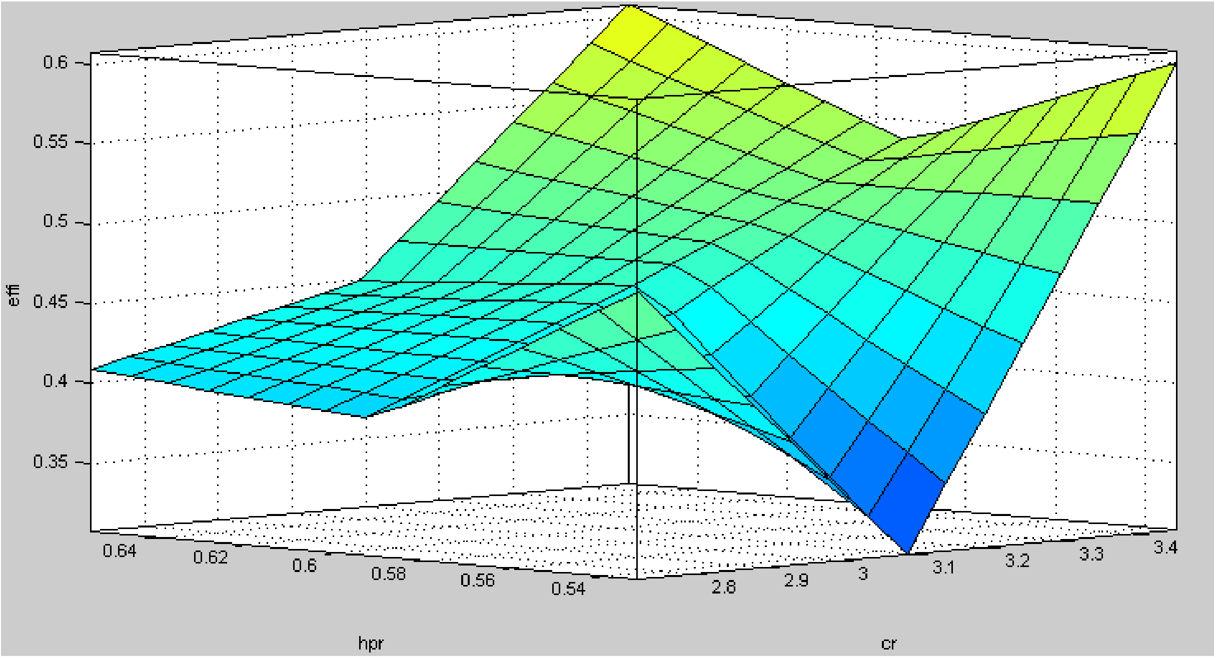

FIG. 7.11: SURFACE FOR 1/LP/E CONFIGURATION FOR EFFICIENCY

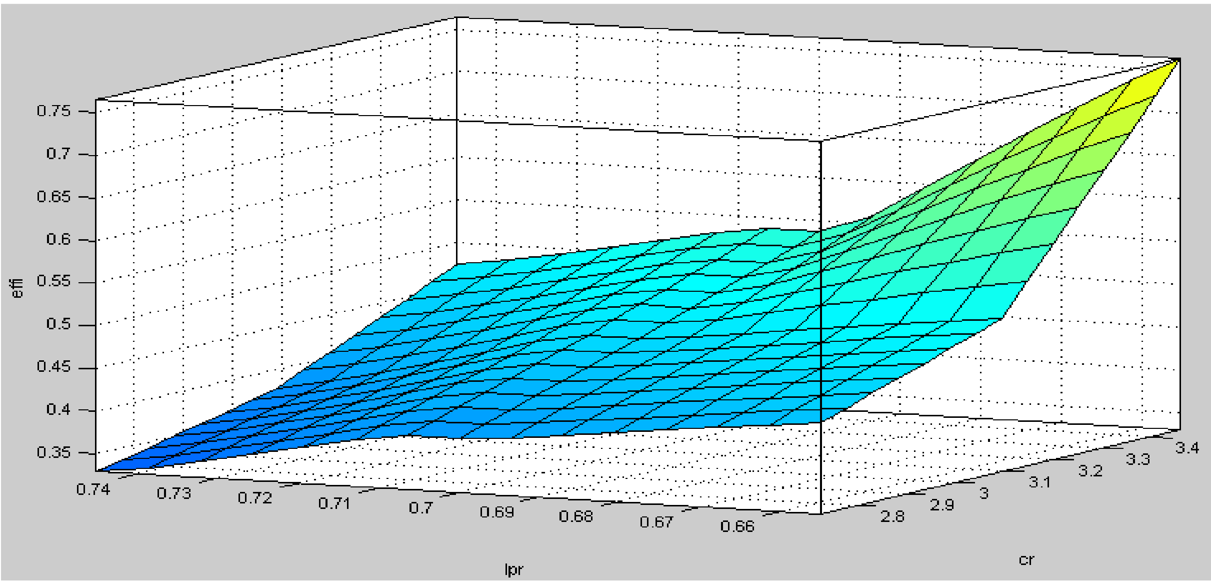

FIG. 7.12: SURFACE FOR 1/LP/E CONFIGURATION FOR SPECFIC WORK DONE

7.5 CONCLUSION

The solution of the optimization problem has been obtained with help of Adaptive Neuro Fuzzy Inference System (ANFIS) in Matlab Software. The training data which is used to train the network is given in Appendix- A. The conclusion drawn from the thesis work is given in the following points:

1. The gas turbine system is considered to be made up of a number of subsystem and the operating state is expressed by design variables that control such subsystems. These design variables are temperature ratios across the compressor, turbine and regenerator which are used to optimized to achieve maximum performance. These temperature ratios are given certain initial values which should satisfy the constraints.
2. The criteria for optimization are thermal efficiency and non-dimensional specific output. The temperature ratio that gives maximum specific output and thermal efficiency are different.
3. The problem of optimization of various gas turbine configuration has been treated as constrained optimization problem with differentiable objective and constraint functions which fully justifies the use of Artificial Neural Networks.
4. The optimum results are obtained with the help of data obtained from the results of Y. Tsujikawa and M. Nagaoka [7].
5. In the design procedure of various gas turbine schemes, an optimum working cycle can be determined by the ANFIS in a short duration of time.
6. The results obtained by ANFIS technique are compared with those obtained by Multiplier Method to show the validity of ANFIS.

7.6 SCOPE OF FUTURE WORK

By presenting the above work it is clear that the technique used is very effective and fast in obtaining the results. As our results are validated the trueness of the technique is verified. So this study can be extended further to the following problems:

1. For the optimum design of the individual components constituting the cycle such as compressors, turbines, regenerators and intercoolers the Adaptive Neuro Fuzzy Inference System (ANFIS) technique can be used effectively.

2. Objective functions can be modified i.e. objective functions may be cost, weight, fuel consumptions and overall efficiency etc.
3. The use of this technique can be extended to the configurations in which intercoolers are employed between the two stages of the compressions and also in the configurations in which the reheaters are introduced in between the two turbines and also for complicated gas turbine configurations in which intercooling, regeneration and reheating are taken together as a single system.
4. The study can be extended to fields other than the gas turbine applications, such as aircraft engines where the objective functions may be maximum overall efficiency, non-dimensional specific output, specific fuel consumption (SFC), non-dimensional thrust etc. of ramjet, turbojet and turbofan engines.
5. As this ANFIS technique requires the data for the training of the network, so this is data based technique. It can be used for the other engineering problems in which the results are experiment based.
6. ANFIS technique is a rule based technique. It uses the if-then rules for deciding the results. So this technique can be used for the optimization of the conditional experimental data.
7. Once we have trained the network then we can use it for testing the experimental data that is we can decide that are the experimental results are in accordance with the trained data.
8. This method of optimization can also be applied to other mechanical engineering problems particularly for the problems which are data and rule based.

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APPENDIX - A

Training data for different configurations.

Training data for efficiency for 1/C configurations.

θ_C	θ_T	efficiency (η_{th})
2.4002	0.5691	0.2901
2.7722	0.3965	0.559
2.1133	0.4261	0.6084
1.9799	0.3321	0.7813
1.7311	0.4462	0.6234
1.6555	0.5926	0.4077
1.6392	0.3311	0.805
1.7399	0.6311	0.3388
2.6359	0.5522	0.2551
3.0031	0.5621	0.0933
2.6655	0.4532	0.4578
1.9351	0.3621	0.7356
1.5621	0.4976	0.5672
2.3963	0.5678	0.2937
1.8333	0.3692	0.7328
2.2468	0.4826	0.4868
2.1234	0.2468	0.9186
1.5544	0.5651	0.4702
3.0066	0.4461	0.3827
3.0111	0.5226	0.189
2.6319	0.4568	0.458
2.7816	0.3279	0.7117
1.6832	0.3396	0.7896
2.963	0.5689	0.0945
2.7962	0.5321	0.2465
1.7366	0.4891	0.557
2.3111	0.4522	0.531
2.3214	0.5489	0.3487
2.6666	0.3657	0.6449
2.1162	0.4226	0.614
1.9622	0.5221	0.4698
2.2299	0.4411	0.5648
2.6331	0.4378	0.4976
1.8621	0.5666	0.4158
2.837	0.4541	0.4126
2.133	0.562	0.3687
2.4	0.5141	0.396
1.833	0.6393	0.3064
2.152	0.5656	0.3581

2.001	0.5962	0.3394
1.317	0.4175	0.7047
1.619	0.4925	0.5674
1.49	0.46	0.6296
2.187	0.715	0.0846
2.497	0.6992	0.0028
1.866	0.76	0.1066
2.199	0.7242	0.0643
2.073	0.7353	0.0856
2.81	0.4551	0.4176
2.811	0.4561	0.415
2.812	0.5561	0.1862
2.942	0.4498	0.3931
1.9991	0.698	0.1702
1.86	0.4444	0.6108
1.7272	0.3441	0.7798
2.9996	0.3663	0.5843
2.7876	0.5111	0.2969
3.0048	0.3005	0.7481
3.101	0.45	0.3418
3.2089	0.5533	0.0137
2.111	0.4231	0.6139
2.6758	0.541	0.2664
1.9967	0.366	0.7236
2	0.3	0.0333
2.5755	0.5755	0.2256
1.6666	0.4444	0.6334
1.7676	0.5676	0.4314
1.9777	0.4678	0.557
1.779	0.45	0.6119
2.01	0.57	0.3813
2.0901	0.4632	0.5478
2.1333	0.4664	0.5354
2.2222	0.5666	0.3401
2.8341	0.4699	0.3769
1.0006	0.6111	0.486
1.6999	0.4622	0.6027
1.8331	0.3322	0.7913
1.9222	0.5777	0.3864
2.7654	0.4678	0.4008
1.8181	0.3794	0.7181
1.9332	0.4677	0.5636
2.7319	0.5332	0.2655
2.9697	0.4224	0.4523
3.3446	0.5992	0.2483
2.6688	0.517	0.3201
2.589	0.533	0.3094

1.868	0.372	0.7254
1.7779	0.391	0.7036
2.7979	0.4321	0.473
2.833	0.5461	0.2014
1.6161	0.459	0.6173
2.3993	0.572	0.2848
1.786	0.459	0.5971

Training data for specific work done for 1/C configurations.

θ_C	θ_T	swd (l) KW/kg sec
2.4002	0.5691	241.38
2.7722	0.3965	398.5
2.1133	0.4261	561.98
1.9799	0.3321	755.07
1.7311	0.4462	652.13
1.6555	0.5926	436.32
1.6392	0.3311	865.7
1.7399	0.6311	353.47
2.6359	0.5522	192.99
3.0031	0.5621	59.65
2.6655	0.4532	342.02
1.9351	0.3621	721.41
1.5621	0.4976	623.97
2.3963	0.5678	244.7
1.8333	0.3692	742.62
2.2468	0.4826	428.86
2.1234	0.2468	845.63
1.5544	0.5651	518.43
3.0066	0.4461	244.13
3.0111	0.5226	120.29
2.6319	0.4568	346.91
2.7816	0.3279	505.25
1.6832	0.3396	838.02
2.963	0.5689	61.6
2.7962	0.5321	173.86
1.7366	0.4891	581.73
2.3111	0.4522	456.98
2.3214	0.5489	298.91
2.6666	0.3657	481.57
2.1162	0.4226	566.66
1.9622	0.5221	456.74
2.2299	0.4411	500.67
2.6331	0.4378	376.93
1.8621	0.5666	417.57

2.837	0.4541	285.6
2.133	0.562	338.24
2.4	0.5141	329.44
1.833	0.6393	310.56
2.152	0.5656	326.4
2.001	0.5962	325.76
1.317	0.4175	830.56
1.619	0.4925	613.92
1.49	0.46	707.2
2.187	0.715	76.16
2.497	0.6992	2.24
1.866	0.76	106.88
2.199	0.7242	57.6
2.073	0.7353	80.16
2.81	0.4551	292.64
2.811	0.4561	290.72
2.812	0.5561	130.4
2.942	0.4498	258.88
1.9991	0.698	163.49
1.86	0.4444	613.76
1.7272	0.3441	816.74
2.9996	0.3663	374.05
2.7876	0.5111	210.21
3.0048	0.3005	477.66
3.101	0.45	207.68
3.2089	0.5533	7.872
2.111	0.4231	567.52
2.6758	0.541	198.14
1.9967	0.366	695.46
2	0.3	800
2.5755	0.5755	175.04
1.6666	0.4444	675.65
1.7676	0.5676	446.21
1.9777	0.4678	538.66
1.779	0.45	630.72
2.01	0.57	364
2.0901	0.4632	510.05
2.1333	0.4664	491.1
2.2222	0.5666	302.34
2.8341	0.4699	261.25
1.0006	0.6111	622.03
1.6999	0.4622	636.51
1.8331	0.3322	801.89
1.9222	0.5777	380.58
2.7654	0.4678	286.59
1.8181	0.3794	731.17
1.9332	0.4677	553.06

2.7319	0.5332	192.67
2.9697	0.4224	293.86
3.3446	0.5992	211.01
2.6688	0.517	238.78
2.589	0.533	238.72
1.868	0.372	727.04
1.7779	0.391	725.47
2.7979	0.4321	333.31
2.833	0.5461	139.68
1.6161	0.459	668.45
2.3993	0.572	237.02
1.786	0.459	614.08

Tarining data for efficiency for 1/C/E configuration

θ_C	θ_T	θ_E	efficiency (ηth)
1.1828	0.6409	1.5612	0.4411
2.1542	0.4462	1.0613	0.5831
1.9805	0.6039	1.3934	0.4374
3.0031	0.5621	1.0012	0.0916
2.6655	0.4532	1.2612	0.6392
2.3963	0.5678	1.5222	0.5542
2.1333	0.4664	1.1937	0.613
1.0006	0.6111	2.3471	0.7185
2.01	0.57	1.3421	0.4852
2.7652	0.4678	1.1342	0.471
1.9222	0.5777	2.1616	0.3794
2	0.3	1.4432	0.1592
1.9332	0.4677	1.1212	0.598
2.6758	0.541	1.4911	0.6007
1.868	0.372	0.9496	0.6902
2.7979	0.4321	1.1151	0.5429
2.0901	0.4632	1.2661	0.6636
2.3993	0.572	1.3111	0.3915
2.3446	0.5992	1	0.2434
1.8181	0.3794	0.9726	0.6929
1.786	0.459	0.9	0.5543
1.7779	0.391	1.1111	0.7346
2.1162	0.4226	1.6216	0.1065
2.1234	0.2468	1.1779	0.0364
2.963	0.5689	1.5256	0.3933
2.2219	0.4526	1.1352	0.5993
2.6331	0.4378	1.0048	0.4903
2.2299	0.4411	1.5621	0.011
2.4002	0.5691	1.3666	0.4298

1.9799	0.3321	1.6628	0.354
2.6319	0.4568	1.4444	0.8865
2.7962	0.5555	1.1199	0.2236
2.6666	0.3657	1.4224	0.2218
2.5667	0.5757	1.2211	0.2914
1.7399	0.6311	1.5577	0.4728
2.7816	0.3279	1.4475	0.5892
1.8732	0.5649	1.3585	0.5198
1.9333	0.7256	1.4129	0.1895
2.0004	0.5	1.6339	0.8487
2.0178	0.4312	1.1234	0.6548
1.868	0.4111	1.1111	0.3149
2.7172	0.2695	1.2316	0.147
3.0007	0.3178	1.7341	0.461
2.7645	0.4555	1.3333	0.7144
1.8667	0.1826	1.4926	0.4256
3.1126	0.2346	1.1356	0.1456
2.5899	0.1134	1.3324	0.7984
1.6472	0.5682	1.1652	0.4809
1.8888	0.4492	1.8142	0.1618
1.9333	0.5336	1.1539	0.495
2.6664	0.4999	1.6446	0.3295
1.9338	0.5001	1.3349	0.6344
1.8752	0.2613	1.7683	0.64
2.3395	0.1458	1.4553	0.8008
1.8645	0.3366	1.4299	0.2977
3.0195	0.5286	1.35	0.3581
1.4149	0.4953	1.2853	0.6495
2.5645	0.5336	1.2111	0.3971
1.9888	0.6266	1.4329	0.4003
1.9	0.6	1.4444	0.4779
1.8466	0.3311	1.2227	0.8927
2.6451	0.4526	1.3721	0.7807
2.9726	0.1197	1.4556	0.5364
2.7541	0.3643	1.7555	0.451
3.0011	0.7211	0.9033	0.2819
2.3355	0.4511	1.5733	0.4169
2.6261	0.5777	1.3221	0.3113
2.9645	0.3412	1.4554	0.9008
3.3216	0.2615	1.5656	0.7074
2.6009	0.1935	1.2632	0.3898
2.7117	0.2666	1.6322	0.3385
2.8818	0.5511	1.312	0.2916
3.3325	0.1296	1.1234	0.5754
1.8621	0.4567	1.934	0.2993
2.7645	0.4555	1.1235	0.4957
2.5965	0.321	1.3666	0.2143

2.4321	0.465	1.7575	0.6787
2.6752	0.3521	1.6626	0.7761
2.8962	0.4221	1.2525	0.7092
2.87	0.5663	1.5525	0.5374
2.9361	0.3362	1.5996	0.4666
2.5652	0.6666	1.4227	0.0739
1.9599	0.2566	1.5331	0.3542
1.963	0.3226	1.4772	0.1311
1.562	0.7622	1.5991	0.2456
2.165	0.3111	1.2233	0.95
3	0.4546	1.1561	0.4651
2.9732	0.4465	1.5321	0.7502
2.8888	0.5963	1.4432	0.153
2.3621	0.8621	1.6592	0.6099
2.5522	0.8	1.6641	0.7188
2.6311	0.4563	1.331	0.7114
2.9581	0.2222	1.442	0.5766
1.9221	0.2562	1.5678	0.3798
1.8777	0.2422	1.3456	0.1535
2.0001	0.2196	1.4726	0.3841
2.0333	0.3005	1.5692	0.3347
1.8181	0.4111	1.2432	0.7606

Tarining data for specific work done for 1/C/E configuration

θ_C	θ_T	θ_E	swd (l) KW/kg sec
1.1828	0.6409	1.5612	308.06
2.1542	0.4462	1.0613	516.74
1.9805	0.6039	1.3934	320
3.0031	0.5621	1.0012	59.65
2.6655	0.4532	1.2612	341.92
2.3963	0.5678	1.5222	244.7
2.1333	0.4664	1.1937	491.1
1.0006	0.6111	2.3471	622.05
2.01	0.57	1.3421	364.8
2.7652	0.4678	1.1342	286.66
1.9222	0.5777	2.1616	380.58
2	0.3	1.4432	800
1.9332	0.4677	1.1212	553.06
2.6758	0.541	1.4911	198.14
1.868	0.372	0.9496	727.04
2.7979	0.4321	1.1151	333.31
2.0901	0.4632	1.2661	510.05
2.3993	0.572	1.3111	237.02
2.3446	0.5992	1	211.01

1.8181	0.3794	0.9726	731.17
1.786	0.459	0.9	614.08
1.7779	0.391	1.1111	725.47
2.1162	0.4226	1.6216	566.66
2.1234	0.2468	1.1779	845.63
2.963	0.5689	1.5256	61.6
2.2219	0.4526	1.1352	484.83
2.6331	0.4378	1.0048	376.93
2.2299	0.4411	1.5621	500.67
2.4002	0.5691	1.3666	241.38
1.9799	0.3321	1.6628	755.07
2.6319	0.4568	1.4444	346.91
2.7962	0.5555	1.1199	136.42
2.6666	0.3657	1.4224	481.57
2.5667	0.5757	1.2211	177.54
1.7399	0.6311	1.5577	353.47
2.7816	0.3279	1.4475	505.25
1.8732	0.5649	1.3585	416.74
1.9333	0.7256	1.4129	140.38
2.0004	0.5	1.6339	479.87
2.0178	0.4312	1.1234	584.38
1.868	0.4111	1.1111	891.04
2.7172	0.2695	1.2316	619.3
3.0007	0.3178	1.7341	451.3
2.7645	0.4555	1.3333	306.56
1.8667	0.1826	1.4926	1030.5
3.1126	0.2346	1.1356	548.61
2.5899	0.1134	1.3324	909.79
1.6472	0.5682	1.1652	483.78
1.8888	0.4492	1.8142	596.86
1.9333	0.5336	1.1539	497.58
2.6664	0.4999	1.6446	266.91
1.9338	0.5001	1.3349	501.02
1.8752	0.2613	1.7683	901.86
2.3395	0.1458	1.4553	938.08
1.8645	0.3366	1.4299	784.8
3.0195	0.5286	1.35	108
1.4149	0.4953	1.2853	674.75
2.5645	0.5336	1.2111	245.6
1.9888	0.6266	1.4329	281.02
1.9	0.6	1.4444	352
1.8466	0.3311	1.2227	799.33
2.6451	0.4526	1.3721	349.41
2.9726	0.1197	1.4556	777.25
2.7541	0.3643	1.7555	455.81
3.0011	0.7211	0.9033	194.11
2.3355	0.4511	1.5733	450.88

2.6261	0.5777	1.3221	155.33
2.9645	0.3412	1.4554	425.44
3.3216	0.2615	1.5656	438.69
2.6009	0.1935	1.2632	778.11
2.7117	0.2666	1.6322	625.7
2.8818	0.5511	1.312	116.06
3.3325	0.1296	1.1234	646.24
1.8621	0.4567	1.934	593.41
2.7645	0.4555	1.1235	306.56
2.5965	0.321	1.3666	575.46
2.4321	0.465	1.7575	397.73
2.6752	0.3521	1.6626	500.58
2.8962	0.4221	1.2525	317.86
2.87	0.5663	1.5525	95.52
2.9361	0.3362	1.5996	442.53
2.5652	0.6666	1.4227	32.58
1.9599	0.2566	1.5331	882.27
1.963	0.3226	1.4772	775.68
1.562	0.7622	1.5991	200.64
2.165	0.3111	1.2233	729.44
3	0.4546	1.1561	232.64
2.9732	0.4465	1.5321	254.18
2.8888	0.5963	1.4432	41.5
2.3621	0.8621	1.6592	215.23
2.5522	0.8	1.6641	176.7
2.6311	0.4563	1.331	347.97
2.9581	0.2222	1.442	617.89
1.9221	0.2562	1.5678	895.01
1.8777	0.2422	1.3456	931.62
2.0001	0.2196	1.4726	928.61
2.0333	0.3005	1.5692	788.54
1.8181	0.4111	1.2432	680.45
2.6421	0.3361	1.26	536.77

Tarining data for efficiency for 1/LP configuration

θ_C	θ_{HT}	θ_{LT}	efficiency (ηth)
0.1456	0.6443	0.6987	0.5128
2.9765	0.6112	0.7331	0.395
2.9888	0.5993	0.7045	0.4705
3.0099	0.6332	0.6982	0.3904
2.8261	0.5773	0.7	0.451
3.1634	0.5331	0.6829	0.54
3.2962	0.6221	0.6982	0.4681
3.0026	0.6131	0.6888	0.3835

2.8451	0.5895	0.7139	0.4883
3.2666	0.6008	0.7125	0.4737
2.9681	0.6337	0.69	0.4434
3	0.5987	0.6977	0.4226
2.8111	0.6456	0.7076	0.413
2.9777	0.59	0.7111	0.5293
3.2211	0.6181	0.6891	0.4275
2.9793	0.6045	0.7015	0.4376
2.8586	0.5826	0.6819	0.4241
3.2678	0.6216	0.7339	0.4679
3.0128	0.6224	0.7199	0.4299
3.1632	0.5999	0.7057	0.471
3.0291	0.631	0.7177	0.4429
2.8654	0.6456	0.7326	0.3963
3.0066	0.6221	0.7011	0.4571
3.1122	0.6111	0.7271	0.4329
2.8954	0.5877	0.6901	0.424
2.7577	0.5982	0.7123	0.3761
2.8888	0.6432	0.6927	0.4587
2.8989	0.6117	0.6888	0.4439
2.9	0.618	0.6772	0.4655
2.9595	0.5933	0.6888	0.4434
2.9876	0.6	0.6972	0.4424
3.0111	0.6321	0.7256	0.4273
3.2444	0.5853	0.6933	0.4995
3.1166	0.585	0.694	0.4657
3.1732	0.5962	0.6969	0.4847
3.2446	0.6126	0.7129	0.4909
3.2555	0.6132	0.7335	0.459
3.2675	0.6321	0.71	0.5185
3.0055	0.6116	0.7233	0.4158
3.1064	0.5804	0.6842	0.4743
2.9173	0.6022	0.7067	0.4155
2.9971	0.6131	0.7278	0.4083
3.1117	0.5874	0.7333	0.4065
2.7444	0.5729	0.6729	0.4071
2.8528	0.5821	0.699	0.3998
2.8001	0.5888	0.7077	0.3833
2.9333	0.5998	0.6963	0.4391
2.9421	0.6199	0.7331	0.394
3.1965	0.6005	0.7222	0.4532
3.4562	0.5793	0.7122	0.4902
3.3333	0.5926	0.7011	0.5291
2.9753	0.5834	0.7269	0.3856
2.7861	0.6229	0.7296	0.3728
2.8809	0.6361	0.7184	0.416
3.2468	0.5951	0.6922	0.5119

3.2444	0.633	0.7066	0.5184
3.1515	0.6066	0.6726	0.5265
3.0222	0.6235	0.6896	0.4795
3.3416	0.5926	0.7216	0.4874
3.2266	0.5972	0.7272	0.4501
3.1999	0.5828	0.6931	0.4869
3.2449	0.6001	0.7333	0.4468
2.9421	0.5984	0.6821	0.453
2.8661	0.582	0.6998	0.4012
2.8752	0.5978	0.7075	0.4032
2.8666	0.6158	0.7441	0.3619
2.9624	0.6312	0.7224	0.4214
3.0975	0.5986	0.6904	0.4773
2.8772	0.6221	0.6924	0.4417
2.9316	0.5874	0.7186	0.3916
2.8427	0.6112	0.7345	0.3686
3.0513	0.5991	0.7449	0.3843
2.9213	0.6116	0.721	0.4022
3.0003	0.5968	0.6832	0.4633
2.8694	0.5744	0.6774	0.4262
2.9771	0.5922	0.6868	0.4493
3.226	0.5901	0.6962	0.4952
2.9326	0.6022	0.7324	0.3819
3.4329	0.6146	0.7011	0.5744
3.3692	0.6322	0.7144	0.5425
2.9755	0.6146	0.6992	0.4474
2.9225	0.6245	0.7145	0.4205
2.8326	0.6555	0.6732	0.4843
2.9134	0.5921	0.7311	0.3739
2.8354	0.5874	0.7426	0.3423
3.0465	0.5876	0.7092	0.4286
3.268	0.5757	0.7116	0.4697
3.0221	0.5906	0.7259	0.401
3.2222	0.6221	0.6864	0.5377
2.9656	0.6321	0.6822	0.4774
2.7258	0.621	0.6911	0.4133
2.7415	0.6017	0.6767	0.422
2.8995	0.58	0.6926	0.4159
2.8627	0.5828	0.6551	0.4608
2.9331	0.5666	0.694	0.411
2.8547	0.5775	0.7385	0.3449
2.9444	0.5928	0.7266	0.3863
2.9721	0.5896	0.7154	0.4054
3.303	0.5999	0.7222	0.4812

Tarining data for specific work done for 1/LP configuration

θC	θHT	θLT	swd (l) KW/kg sec
3.1456	0.6443	0.6987	310.6
2.9765	0.6112	0.7331	261.01
2.9888	0.5993	0.7045	283.35
3.0099	0.6332	0.6982	305.76
2.8261	0.5773	0.7	277.1
3.1634	0.5331	0.6829	270.47
3.2962	0.6221	0.6982	300.4
3.0026	0.6131	0.6888	305.27
2.8451	0.5895	0.7139	269.85
3.2666	0.6008	0.7125	276.37
2.9681	0.6337	0.69	314.16
3	0.5987	0.6977	289.58
2.8111	0.6456	0.7076	302.04
2.9777	0.59	0.7111	272.72
3.2211	0.6181	0.6891	307.47
2.9793	0.6045	0.7015	288.71
2.8586	0.5826	0.6819	296.52
3.2678	0.6216	0.7339	264.65
3.0128	0.6224	0.7199	278.93
3.1632	0.5999	0.7057	282.48
3.0291	0.631	0.7177	285.01
2.8654	0.6456	0.7326	276.21
3.0066	0.6221	0.7011	297.51
3.1122	0.6111	0.7271	266.83
2.8954	0.5877	0.6901	291.41
2.7577	0.5982	0.7123	275.36
2.8888	0.6432	0.6927	316.25
2.8989	0.6117	0.6888	304.58
2.9	0.618	0.6772	319.18
2.9595	0.5933	0.6888	295.42
2.9876	0.6	0.6972	290.69
3.0111	0.6321	0.7256	277.52
3.2444	0.5835	0.6933	286.34
3.1166	0.585	0.694	286.42
3.1732	0.5962	0.6969	289.13
3.2446	0.6126	0.7129	281.4
3.2555	0.6132	0.7335	261.47
3.2675	0.6321	0.71	293.29
3.0055	0.6116	0.7233	270.77
3.1064	0.5804	0.6842	293.26
2.9173	0.6022	0.7067	282.6
2.9971	0.6131	0.7278	267.02
3.1117	0.5874	0.7333	250.66

2.7444	0.5729	0.6729	299.83
2.8528	0.5821	0.699	280.34
2.8001	0.5888	0.7077	275.37
2.9333	0.5998	0.6963	291.45
2.9421	0.6199	0.7331	264.72
3.1965	0.6005	0.7222	266.91
3.4562	0.5793	0.7122	266.76
3.3333	0.5926	0.7011	266.76
2.9753	0.5834	0.7269	254.92
2.7861	0.6229	0.7296	269.49
2.8809	0.6361	0.7184	286.01
3.2468	0.5951	0.6922	269.07
3.2444	0.633	0.7066	297.16
3.1515	0.6066	0.6726	317.76
3.0222	0.6235	0.6896	309.66
3.3416	0.5926	0.7216	263.97
3.2266	0.5972	0.7272	260.66
3.1999	0.5828	0.6931	286.18
3.2449	0.6001	0.7333	256.07
2.9421	0.5984	0.6821	304.37
2.8661	0.582	0.6998	279.55
2.8752	0.5978	0.7075	279.77
2.8666	0.6158	0.7441	252.13
2.9624	0.6312	0.7224	280.35
3.0975	0.5986	0.6904	296.52
2.8772	0.6221	0.6924	306.17
2.9316	0.5874	0.7186	264.47
2.8427	0.6112	0.7345	259.64
3.0513	0.5991	0.7449	244.53
2.9213	0.6116	0.721	273.02
3.0003	0.5968	0.6832	302.51
2.8694	0.5744	0.6774	296.48
2.9771	0.5922	0.6868	296.76
3.226	0.5901	0.6962	286.84
2.9326	0.6022	0.7324	293.93
3.4329	0.6146	0.7011	257.84
3.3692	0.6322	0.7144	288.89
2.9755	0.6146	0.6992	295.79
2.9225	0.6245	0.7145	285.27
2.8326	0.6555	0.6732	342.75
2.9134	0.5921	0.7311	254.74
2.8354	0.5874	0.7426	241.91
3.0465	0.5876	0.7092	273.4
3.268	0.5757	0.7116	265.65
3.0221	0.5906	0.7259	259.01
3.2222	0.6221	0.6864	312.14
2.9656	0.6321	0.6822	317.16

2.7258	0.621	0.6911	306.92
2.7415	0.6017	0.6767	311.25
2.8995	0.58	0.6926	285.27
2.8627	0.5828	0.6551	321.61
2.9331	0.5666	0.694	277.41
2.8547	0.5775	0.7385	241.62
2.9444	0.5928	0.7266	259.31
2.9721	0.5896	0.7154	268.48
3.303	0.5999	0.7222	266.64

Tarining data for efficiency for 1/LP/E configuration

θ_C	θ_E	θ_{HT}	θ_{LT}	η_{th}
2.1828	1.6409	0.7612	0.7411	0.6809
2.1542	1.4462	0.7613	0.7331	0.5283
1.9805	1.6039	0.7934	0.7374	0.5599
2.0031	1.5621	0.8012	0.7216	0.5842
2.2655	1.4532	0.8612	0.7692	0.5703
2.2963	1.5678	0.7222	0.7542	0.6214
2.1333	1.4664	0.7937	0.763	0.4924
2.0006	1.6111	0.8471	0.7285	0.6342
2.01	1.57	0.7421	0.7752	0.4432
2.1652	1.4678	0.8342	0.751	0.5586
1.9222	1.5777	0.7616	0.7594	0.4564
2	1.3	0.7432	0.7592	0.3654
1.9332	1.4677	0.8212	0.768	0.4317
2.3758	1.541	0.7911	0.7607	0.6928
1.868	1.372	0.7496	0.7502	0.3765
2.1979	1.4321	0.8151	0.7429	0.5543
2.0901	1.4632	0.7661	0.7636	0.457
2.1993	1.572	0.8111	0.7215	0.7175
2.2446	1.5992	0.8	0.7434	0.7132
1.8181	1.3794	0.7726	0.7329	0.4057
1.886	1.459	0.8001	0.7543	0.4284
1.9779	1.391	0.7111	0.7346	0.4112
2.1162	1.4226	0.8216	0.7035	0.6
2.1234	1.4468	0.7779	0.7364	0.5281
2.063	1.5689	0.8256	0.7333	0.6118
2.2219	1.4526	0.8352	0.7593	0.5558
2.1331	1.4378	0.8048	0.7403	0.5298
2.0002	1.5691	0.7666	0.7298	0.5452
1.9799	1.3321	0.7628	0.754	0.3892
2.2319	1.4568	0.7444	0.7465	0.5288
2.1962	1.5555	0.8199	0.7236	0.7011
2.1666	1.3657	0.8224	0.7218	0.5492

2.0667	1.5757	0.8211	0.7214	0.6429
1.9399	1.6311	0.7577	0.7428	0.5202
2.0816	1.3279	0.8075	0.7592	0.4261
1.8732	1.5649	0.7585	0.7598	0.4316
1.9333	1.7256	0.8129	0.7395	0.6236
2.0004	1.5	0.7639	0.7487	0.4705
2.0178	1.4312	0.8234	0.7548	0.4684
1.868	1.4111	0.8111	0.7349	0.4457
2.2172	1.2695	0.8016	0.747	0.4547
2.0007	1.3178	0.7941	0.741	0.4264
2.0645	1.4555	0.7833	0.7344	0.511
1.8667	1.1826	0.7926	0.7456	0.3538
2.1126	1.2346	0.7956	0.7456	0.4146
2.1899	1.1134	0.7824	0.7384	0.3915
1.9472	1.5682	0.7652	0.7409	0.4991
1.8888	1.4492	0.8142	0.7618	0.42
1.9333	1.5336	0.7539	0.745	0.4629
2.0664	1.4999	0.7746	0.7295	0.5474
1.9338	1.5001	0.8049	0.7644	0.4891
1.8752	1.2613	0.7683	0.76	0.3425
2.2395	1.1458	0.7553	0.7308	0.4093
1.8645	1.3366	0.7699	0.7277	0.4096
2.0195	1.5286	0.78	0.7581	0.4833
1.9149	1.4953	0.7853	0.7495	0.4511
2.1645	1.5336	0.8111	0.7371	0.6218
1.9888	1.6266	0.8129	0.7403	0.5861
1.9	1.6	0.7544	0.7479	0.4755
1.8466	1.3311	0.8227	0.7327	0.4239
2.1451	1.4526	0.7721	0.7507	0.5006
1.9726	1.1197	0.7556	0.7564	0.3231
2.0011	1.7211	0.8033	0.7219	0.7035
2.1355	1.4511	0.7733	0.7469	0.5044
2.2261	1.5777	0.8221	0.7213	0.7546
1.9645	1.3412	0.7554	0.7408	0.4056
2.1216	1.2615	0.7656	0.7274	0.4401
2.0009	1.1935	0.7632	0.7398	0.3725
2.1117	1.2666	0.7322	0.7385	0.4035
1.8818	1.5511	0.812	0.7216	0.5322
2.2325	1.1296	0.8234	0.7554	0.3982
1.8621	1.4567	0.804	0.7293	0.4602
2.0645	1.4555	0.8235	0.7457	0.5143
2.5965	1.321	0.7666	0.7243	0.6596
2.1321	1.465	0.7775	0.7687	0.2637
2.2752	1.3521	0.7626	0.7461	0.4932
1.8962	1.4221	0.7625	0.7292	0.4392
1.87	1.5663	0.7825	0.7374	0.4862
2.1361	1.3362	0.7996	0.7466	0.4627

2.0652	1.6666	0.7227	0.7339	0.6048
1.9599	1.2566	0.8331	0.7542	0.3955
1.963	1.3226	0.7772	0.7311	0.426
1.862	1.7622	0.7991	0.7456	0.5796
2.165	1.3111	0.7233	0.7505	0.4091
2	1.4546	0.7861	0.7451	0.4678
2.1732	1.4465	0.7921	0.7402	0.5432
2.2888	1.5963	0.7743	0.753	0.696
2.0621	1.8621	0.7592	0.7299	0.8661
2.1522	1.8	0.7641	0.7188	0.935
1.866	1.517	0.8297	0.76	0.44
2.2311	1.4563	0.791	0.7114	0.6389
1.9581	1.2222	0.782	0.7566	0.3578
1.9221	1.2562	0.7678	0.7398	0.3786
1.8777	1.2422	0.7956	0.7535	0.3602
2.0001	1.2196	0.7726	0.7341	0.3931
2.0333	1.3005	0.7692	0.7347	0.4245
1.8181	1.4111	0.7832	0.7606	0.3774

Tarining data for specific work done for 1/LP/E configuration

θ_C	θ_E	θ_{HT}	θ_{LT}	swd(l)
2.1828	1.6409	0.7612	0.7411	315.2
2.1542	1.4462	0.7613	0.7331	325.1
1.9805	1.6039	0.7934	0.7374	333.35
2.0031	1.5621	0.8012	0.7216	356.89
2.2655	1.4532	0.8612	0.7692	318.02
2.2963	1.5678	0.8222	0.7542	284.03
2.1333	1.4664	0.8937	0.763	300.97
2.0006	1.6111	0.8471	0.7285	367.98
2.01	1.57	0.7421	0.7752	266.92
2.1652	1.4678	0.8342	0.751	332.34
1.9222	1.5777	0.7616	0.7594	293.18
2	1.3	0.7432	0.7592	286.34
1.9332	1.4677	0.8212	0.768	304.83
2.3758	1.541	0.7911	0.7607	302.9
1.868	1.372	0.7496	0.7502	299.6
2.1979	1.4321	0.8151	0.7429	335.3
2.0901	1.4632	0.7661	0.7636	289.77
2.1993	1.572	0.8111	0.7215	361.43
2.2446	1.5992	0.8	0.7434	328.45
1.8181	1.3794	0.7726	0.7329	330.18
1.886	1.459	0.8001	0.7543	314.54
1.9779	1.391	0.7111	0.7346	301.96
2.1162	1.4226	0.8216	0.7035	389.77

2.1234	1.4468	0.7779	0.7364	332.44
2.063	1.5689	0.8256	0.7333	352.3
2.2219	1.4526	0.8352	0.7593	321.65
2.1331	1.4378	0.8048	0.7403	334.41
2.2299	1.4411	0.7621	0.721	340.2
2.0002	1.5691	0.7666	0.7298	331.42
1.9799	1.3321	0.7628	0.754	300.24
2.2319	1.4568	0.7444	0.7465	301.93
2.1962	1.5555	0.8199	0.7236	362.59
2.1666	1.3657	0.8224	0.7218	366.07
2.0667	1.5757	0.8211	0.7214	366.01
1.9399	1.6311	0.7577	0.7428	311.81
2.0816	1.3279	0.8075	0.7592	311.11
1.8732	1.5649	0.7585	0.7598	291.51
1.9333	1.7256	0.8129	0.7395	338.82
2.0004	1.5	0.7639	0.7487	307.15
2.0178	1.4312	0.8234	0.7548	323.04
1.868	1.4111	0.8111	0.7349	344.04
2.2172	1.2695	0.8016	0.747	324.49
2.0007	1.3178	0.7941	0.741	329.08
2.0645	1.4555	0.7833	0.7344	332.87
1.8667	1.1826	0.7926	0.7456	322.62
2.1126	1.2346	0.7956	0.7456	323.84
2.1899	1.1134	0.7824	0.7384	327.48
1.9472	1.5682	0.7652	0.7409	317.22
2.073	1.3	0.7892	0.7353	342.29
1.8888	1.4492	0.8142	0.7618	310.31
1.9333	1.5336	0.7539	0.745	307.59
2.0664	1.4999	0.7746	0.7295	339.71
1.9338	1.5001	0.8049	0.7644	335.25
1.8752	1.2613	0.7683	0.76	295.03
2.2395	1.1458	0.7553	0.7308	325.32
1.8645	1.3366	0.7699	0.7277	335.43
2.0195	1.5286	0.78	0.7581	301.89
1.9149	1.4953	0.7853	0.7495	314.75
2.1645	1.5336	0.8111	0.7371	341.18
1.9888	1.6266	0.8129	0.7403	337.78
1.9	1.6	0.7544	0.7479	304.29
1.8466	1.3311	0.8227	0.7327	351.85
2.1451	1.4526	0.7721	0.7507	307.98
1.9726	1.1197	0.7556	0.7564	294.5
2.0011	1.7211	0.8033	0.7219	357.44
2.1355	1.4511	0.7733	0.7469	313.15
2.2261	1.5777	0.8221	0.7213	366.59
1.9645	1.3412	0.7554	0.7408	313.28
2.1216	1.2615	0.7656	0.7274	333.92
2.0009	1.1935	0.7632	0.7398	317.74

2.1117	1.2666	0.7322	0.7385	306.35
1.8818	1.5511	0.812	0.7216	361.7
2.2325	1.1296	0.8234	0.7554	322.24
1.8621	1.4567	0.804	0.7293	348.23
2.0645	1.4555	0.8235	0.7457	335.06
2.5965	1.321	0.7666	0.7243	338.16
2.1321	1.465	0.7775	0.7687	287.74
2.2752	1.3521	0.7626	0.7461	309.8
1.8962	1.4221	0.7625	0.7292	330.6
2.199	1.194	0.7645	0.7242	345.5
1.87	1.5663	0.7825	0.7374	328.78
2.1361	1.3362	0.7996	0.7466	324.19
2.0652	1.6666	0.7227	0.7339	307.7
1.9599	1.2566	0.8331	0.7542	327.64
1.963	1.3226	0.7772	0.7311	334.38
1.862	1.7622	0.7991	0.7456	325.26
2.165	1.3111	0.7233	0.7505	288.74
2	1.4546	0.7861	0.7451	319.34
2.1732	1.4465	0.7921	0.7402	329.26
2.2888	1.5963	0.7743	0.753	306
2.0621	1.8621	0.7592	0.7299	328.1
2.1522	1.8	0.7641	0.7188	343.78
2.2311	1.4563	0.791	0.7114	365.25
1.9581	1.2222	0.782	0.7566	304.54
1.9221	1.2562	0.7678	0.7398	319.65
1.8777	1.2422	0.7956	0.7535	313.78
2.0001	1.2196	0.7726	0.7341	378.69
2.0333	1.3005	0.7692	0.7347	326.51
1.8181	1.4111	0.7832	0.7606	300

APPENDIX – B

Matlab Code for Different Configurations of Gas Turbine Cycle.

Code for efficiency for 1/C configuration

```
[System]
Name='2'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='input1'
Range=[1.0006 3.3446]
Constraintfun1cef
NumMFs=3
MF1='in1mf1':'trimf',[-0.1714 1.01697400419004 2.27538106656816]
MF2='in1mf2':'trimf',[1.0088559923359 2.18551294584952 3.34413078469647]
MF3='in1mf3':'trimf',[2.19715339153566 3.34485534173566 4.51659975089394]

[Input2]
Name='input2'
Range=[0.2468 0.76]
NumMFs=3
MF1='in2mf1':'trimf',[-0.00985600834773433 0.268102439634278
0.548830211359686]
MF2='in2mf2':'trimf',[0.223187762571203 0.504730097528844
0.767357131962216]
MF3='in2mf3':'trimf',[0.560739500537892 0.691501507885824
1.01656992103708]

[Output1]
Name='output'
Range=[2.24 865.7]
NumMFs=9
MF1='out1mf1':'constant',[1254.82254028885]
MF2='out1mf2':'constant',[710.172458027694]
MF3='out1mf3':'constant',[550.799697207632]
MF4='out1mf4':'constant',[844.18488073043]
MF5='out1mf5':'constant',[320.445637887566]
MF6='out1mf6':'constant',[-60.0621145171457]
MF7='out1mf7':'constant',[511.502554477687]
MF8='out1mf8':'constant',[-20.2534237636333]
MF9='out1mf9':'constant',[457.092103126852]
```

```
[Rules]
1 1, 1 (1) : 1
1 2, 2 (1) : 1
1 3, 3 (1) : 1
2 1, 4 (1) : 1
2 2, 5 (1) : 1
2 3, 6 (1) : 1
3 1, 7 (1) : 1
3 2, 8 (1) : 1
3 3, 9 (1) : 1
```

Code for specific work done for 1/C configuration

```
[System]
Name='1C_swd'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='cr'
Range=[1.0006 3.3446]
Constraintfun1cswd
NumMFs=3
MF1='in1mf1':'trimf',[-0.1714 1.01697400419004 2.27538106656816]
MF2='in1mf2':'trimf',[1.0088559923359 2.18551294584952 3.34413078469647]
MF3='in1mf3':'trimf',[2.19715339153566 3.34485534173566 4.51659975089394]

[Input2]
Name='tr'
Range=[0.2468 0.76]
NumMFs=3
MF1='in2mf1':'trimf',[-0.00985600834773433 0.268102439634278
0.548830211359686]
MF2='in2mf2':'trimf',[0.223187762571203 0.504730097528844 0.767357131962216]
MF3='in2mf3':'trimf',[0.560739500537892 0.691501507885824 1.01656992103708]

[Output1]
Name='swd'
Range=[2.24 865.7]
NumMFs=9
MF1='out1mf1':'constant',[1254.82254028885]
MF2='out1mf2':'constant',[710.172458027694]
MF3='out1mf3':'constant',[550.799697207632]
```

```
MF4='out1mf4':'constant',[844.18488073043]
MF5='out1mf5':'constant',[320.445637887566]
MF6='out1mf6':'constant',[-60.0621145171457]
MF7='out1mf7':'constant',[511.502554477687]
MF8='out1mf8':'constant',[-20.2534237636333]
MF9='out1mf9':'constant',[457.092103126852]

[Rules]
1 1, 1 (1) : 1
1 2, 2 (1) : 1
1 3, 3 (1) : 1
2 1, 4 (1) : 1
2 2, 5 (1) : 1
2 3, 6 (1) : 1
3 1, 7 (1) : 1
3 2, 8 (1) : 1
3 3, 9 (1) : 1
```

Code for efficiency for 1/C/E configuration

```
[System]
Name='1CE_eff'
Type='sugeno'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=27
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='cr'
Range=[1.0006 3.3325]
Constraintfun1ceef
NumMFs=3
MF1='in1mf1':'trimf',[-0.165349999416209 1.00485827588474 2.21612780681531]
MF2='in1mf2':'trimf',[0.996684062518279 2.17056955850975 3.33319384486025]
MF3='in1mf3':'trimf',[2.20032473132442 3.33219147773337 4.49845000044142]

[Input2]
Name='tr'
Range=[0.1134 0.8621]
NumMFs=3
MF1='in2mf1':'trimf',[-0.260933581043235 0.129074412292723 0.470175261899284]
MF2='in2mf2':'trimf',[0.10139697325914 0.51501713276537 0.84753292480282]
MF3='in2mf3':'trimf',[0.4575512842778 0.8689363358754 1.23645]

[Input3]
Name='rr'
Range=[0.9 2.3471]
NumMFs=3
```

```
MF1='in3mf1':'trimf',[0.17645 0.890804756719226 1.6181342357478]
MF2='in3mf2':'trimf',[0.903295352610484 1.62306836557984 2.35069730599893]
MF3='in3mf3':'trimf',[1.4543624676679 2.34273655689008 3.07064999915388]

[Output1]
Name='effi'
Range=[0.011 0.95]
NumMFs=27
MF1='out1mf1':'constant',[5.66184484745554]
MF2='out1mf2':'constant',[-4.54248673658561]
MF3='out1mf3':'constant',[28.2139131778664]
MF4='out1mf4':'constant',[-0.745020771627617]
MF5='out1mf5':'constant',[2.63175230684896]
MF6='out1mf6':'constant',[-7.43374409439597]
MF7='out1mf7':'constant',[2.22713833682692]
MF8='out1mf8':'constant',[-3.47170251907309]
MF9='out1mf9':'constant',[16.2646747272306]
MF10='out1mf10':'constant',[-0.758659053676032]
MF11='out1mf11':'constant',[1.30272391228043]
MF12='out1mf12':'constant',[-5.88240022974373]
MF13='out1mf13':'constant',[1.12311679669207]
MF14='out1mf14':'constant',[-0.0553691375428964]
MF15='out1mf15':'constant',[2.30154766849112]
MF16='out1mf16':'constant',[-1.61156850883992]
MF17='out1mf17':'constant',[1.64543208738442]
MF18='out1mf18':'constant',[-3.40240399131887]
MF19='out1mf19':'constant',[0.597865438399765]
MF20='out1mf20':'constant',[0.186543994590281]
MF21='out1mf21':'constant',[2.7792321105447]
MF22='out1mf22':'constant',[-0.419122875824357]
MF23='out1mf23':'constant',[1.78302179016307]
MF24='out1mf24':'constant',[-3.11807049981083]
MF25='out1mf25':'constant',[1.19527508592244]
MF26='out1mf26':'constant',[-4.2855273606133]
MF27='out1mf27':'constant',[21.2760696239892]

[Rules]
1 1 1, 1 (1) : 1
1 1 2, 2 (1) : 1
1 1 3, 3 (1) : 1
1 2 1, 4 (1) : 1
1 2 2, 5 (1) : 1
1 2 3, 6 (1) : 1
1 3 1, 7 (1) : 1
1 3 2, 8 (1) : 1
1 3 3, 9 (1) : 1
2 1 1, 10 (1) : 1
2 1 2, 11 (1) : 1
2 1 3, 12 (1) : 1
2 2 1, 13 (1) : 1
2 2 2, 14 (1) : 1
2 2 3, 15 (1) : 1
2 3 1, 16 (1) : 1
2 3 2, 17 (1) : 1
2 3 3, 18 (1) : 1
3 1 1, 19 (1) : 1
```

```
3 1 2, 20 (1) : 1
3 1 3, 21 (1) : 1
3 2 1, 22 (1) : 1
3 2 2, 23 (1) : 1
3 2 3, 24 (1) : 1
3 3 1, 25 (1) : 1
3 3 2, 26 (1) : 1
3 3 3, 27 (1) : 1
```

Code for specific work done for 1/C/E configuration

```
[System]
Name='1CE_swd'
Type='sugeno'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=27
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='cr'
Range=[1.0006 3.3325]
Constraintfun1ceswd
NumMFs=3
MF1='in1mf1':'trimf',[-0.16535000004594 1.00258293429025 2.16709049907285]
MF2='in1mf2':'trimf',[0.998637411725886 2.16693431356096 3.33385233561156]
MF3='in1mf3':'trimf',[2.15296300125291 3.3309015797421 4.49845000079613]

[Input2]
Name='tr'
Range=[0.1134 0.8621]
NumMFs=3
MF1='in2mf1':'trimf',[-0.260952497329864 0.134126237508496 0.551942142499166]
MF2='in2mf2':'trimf',[0.0920879347503977 0.504979741725503 0.85897905444657]
MF3='in2mf3':'trimf',[0.560419921335562 0.858663239282831 1.23645]

[Input3]
Name='rr'
Range=[0.9 2.3471]
NumMFs=3
MF1='in3mf1':'trimf',[0.17645 0.903900976897217 1.6236818878911]
MF2='in3mf2':'trimf',[0.903913230508323 1.627072134063 2.34708969930373]
MF3='in3mf3':'trimf',[1.61076131751563 2.34672104979325 3.07065000000001]

[Output1]
Name='swd'
Range=[32.58 1030.5]
NumMFs=27
MF1='out1mf1':'constant',[1425.1570451301]
```

```
MF2='out1mf2':'constant',[1512.66636012424]
MF3='out1mf3':'constant',[967.554832055868]
MF4='out1mf4':'constant',[852.898640515067]
MF5='out1mf5':'constant',[607.682221623666]
MF6='out1mf6':'constant',[461.501194405292]
MF7='out1mf7':'constant',[-3053.37151455363]
MF8='out1mf8':'constant',[-151.566769093241]
MF9='out1mf9':'constant',[1288.79795780884]
MF10='out1mf10':'constant',[1090.51966911742]
MF11='out1mf11':'constant',[1086.04849557338]
MF12='out1mf12':'constant',[1203.08439491944]
MF13='out1mf13':'constant',[356.933836029999]
MF14='out1mf14':'constant',[338.428794486344]
MF15='out1mf15':'constant',[508.712707450178]
MF16='out1mf16':'constant',[-542.229356524918]
MF17='out1mf17':'constant',[468.640619970514]
MF18='out1mf18':'constant',[-1984.50602684989]
MF19='out1mf19':'constant',[715.386284978819]
MF20='out1mf20':'constant',[705.484013736906]
MF21='out1mf21':'constant',[1076.01416787537]
MF22='out1mf22':'constant',[-53.1486445451424]
MF23='out1mf23':'constant',[-20.7149694960549]
MF24='out1mf24':'constant',[-524.754515378376]
MF25='out1mf25':'constant',[616.861223348353]
MF26='out1mf26':'constant',[-1582.0663087202]
MF27='out1mf27':'constant',[19500.015939795]

[Rules]
1 1 1, 1 (1) : 1
1 1 2, 2 (1) : 1
1 1 3, 3 (1) : 1
1 2 1, 4 (1) : 1
1 2 2, 5 (1) : 1
1 2 3, 6 (1) : 1
1 3 1, 7 (1) : 1
1 3 2, 8 (1) : 1
1 3 3, 9 (1) : 1
2 1 1, 10 (1) : 1
2 1 2, 11 (1) : 1
2 1 3, 12 (1) : 1
2 2 1, 13 (1) : 1
2 2 2, 14 (1) : 1
2 2 3, 15 (1) : 1
2 3 1, 16 (1) : 1
2 3 2, 17 (1) : 1
2 3 3, 18 (1) : 1
3 1 1, 19 (1) : 1
3 1 2, 20 (1) : 1
3 1 3, 21 (1) : 1
3 2 1, 22 (1) : 1
3 2 2, 23 (1) : 1
3 2 3, 24 (1) : 1
3 3 1, 25 (1) : 1
3 3 2, 26 (1) : 1
3 3 3, 27 (1) : 1
```

Code for efficiency for 1/LP configuration

```
[System]
Name='1LP_eff'
Type='sugeno'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=27
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='cr'
Range=[2.7258 3.4562]
Constraintfun1lpef
NumMFs=3
MF1='in1mf1':'trimf',[2.3606 2.72581202674522 3.09115139719202]
MF2='in1mf2':'trimf',[2.72576995440904 3.09102768931443 3.45618407058591]
MF3='in1mf3':'trimf',[3.09061607390448 3.45621566256921 3.8214]

[Input2]
Name='hpr'
Range=[0.5331 0.6555]
NumMFs=3
MF1='in2mf1':'trimf',[0.4719 0.533033685115966 0.591323510438617]
MF2='in2mf2':'trimf',[0.533145194580731 0.594365064320848 0.655368519566025]
MF3='in2mf3':'trimf',[0.59485293286245 0.655631379204882 0.7167]

[Input3]
Name='lpr'
Range=[0.6551 0.7449]
NumMFs=3
MF1='in3mf1':'trimf',[0.6102 0.654669836002876 0.697243760950436]
MF2='in3mf2':'trimf',[0.655532508097468 0.700777794081941 0.743662629113779]
MF3='in3mf3':'trimf',[0.708891161306699 0.746107958079065 0.7898]

[Output1]
Name='effi'
Range=[0.3423 0.5744]
NumMFs=27
MF1='out1mf1':'constant',[0.286541810935517]
MF2='out1mf2':'constant',[0.486218520328354]
MF3='out1mf3':'constant',[0.211238574142882]
MF4='out1mf4':'constant',[0.434872629598265]
MF5='out1mf5':'constant',[0.393221212153714]
MF6='out1mf6':'constant',[0.329287593564321]
MF7='out1mf7':'constant',[0.518280089864305]
MF8='out1mf8':'constant',[0.408357100728219]
MF9='out1mf9':'constant',[0.342563028964656]
MF10='out1mf10':'constant',[0.588129494265859]
MF11='out1mf11':'constant',[0.306846638508555]
```

```
MF12='out1mf12':'constant',[0.447107901067986]
MF13='out1mf13':'constant',[0.508559884678903]
MF14='out1mf14':'constant',[0.461284193356625]
MF15='out1mf15':'constant',[0.378706245237046]
MF16='out1mf16':'constant',[0.572340956693938]
MF17='out1mf17':'constant',[0.44875573456021]
MF18='out1mf18':'constant',[0.468844570484115]
MF19='out1mf19':'constant',[1.91910108372666]
MF20='out1mf20':'constant',[0.600304077357958]
MF21='out1mf21':'constant',[-1.47196667917606]
MF22='out1mf22':'constant',[0.765158031890562]
MF23='out1mf23':'constant',[0.537453255968322]
MF24='out1mf24':'constant',[0.475365824960888]
MF25='out1mf25':'constant',[0.0417466046028933]
MF26='out1mf26':'constant',[0.607469243362751]
MF27='out1mf27':'constant',[0.520448475544351]

[Rules]
1 1 1, 1 (1) : 1
1 1 2, 2 (1) : 1
1 1 3, 3 (1) : 1
1 2 1, 4 (1) : 1
1 2 2, 5 (1) : 1
1 2 3, 6 (1) : 1
1 3 1, 7 (1) : 1
1 3 2, 8 (1) : 1
1 3 3, 9 (1) : 1
2 1 1, 10 (1) : 1
2 1 2, 11 (1) : 1
2 1 3, 12 (1) : 1
2 2 1, 13 (1) : 1
2 2 2, 14 (1) : 1
2 2 3, 15 (1) : 1
2 3 1, 16 (1) : 1
2 3 2, 17 (1) : 1
2 3 3, 18 (1) : 1
3 1 1, 19 (1) : 1
3 1 2, 20 (1) : 1
3 1 3, 21 (1) : 1
3 2 1, 22 (1) : 1
3 2 2, 23 (1) : 1
3 2 3, 24 (1) : 1
3 3 1, 25 (1) : 1
3 3 2, 26 (1) : 1
3 3 3, 27 (1) : 1
```

Code for specific work done for 1/LP configuration

```
[System]
Name='1LP_swd'
Type='sugeno'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=27
```

```
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='cr'
Range=[2.7258 3.4562]
Constraintfun1lpswd
NumMFs=3
MF1='in1mf1':'trimf',[2.3606 2.7258 3.091]
MF2='in1mf2':'trimf',[2.7258 3.091 3.4562]
MF3='in1mf3':'trimf',[3.091 3.4562 3.8214]

[Input2]
Name='hpr'
Range=[0.5331 0.6555]
NumMFs=3
MF1='in2mf1':'trimf',[0.4719 0.5331 0.5943]
MF2='in2mf2':'trimf',[0.5331 0.5943 0.6555]
MF3='in2mf3':'trimf',[0.5943 0.6555 0.7167]

[Input3]
Name='lpr'
Range=[0.6551 0.7449]
NumMFs=3
MF1='in3mf1':'trimf',[0.6102 0.6551 0.7]
MF2='in3mf2':'trimf',[0.6551 0.7 0.7449]
MF3='in3mf3':'trimf',[0.7 0.7449 0.7898]

[Output1]
Name='swd'
Range=[241.62 342.75]
NumMFs=27
MF1='out1mf1':'constant',[269.791690736245]
MF2='out1mf2':'constant',[291.430971708306]
MF3='out1mf3':'constant',[157.319427810848]
MF4='out1mf4':'constant',[332.720753886253]
MF5='out1mf5':'constant',[276.560436231428]
MF6='out1mf6':'constant',[259.069544929934]
MF7='out1mf7':'constant',[373.505568379622]
MF8='out1mf8':'constant',[317.133547852786]
MF9='out1mf9':'constant',[260.268373139137]
MF10='out1mf10':'constant',[310.87715309521]
MF11='out1mf11':'constant',[226.343115934989]
MF12='out1mf12':'constant',[207.486629423826]
MF13='out1mf13':'constant',[328.367583047289]
MF14='out1mf14':'constant',[290.936510527971]
MF15='out1mf15':'constant',[243.182816854013]
MF16='out1mf16':'constant',[330.908865142102]
MF17='out1mf17':'constant',[316.268233651965]
MF18='out1mf18':'constant',[259.901670850763]
MF19='out1mf19':'constant',[-110.032014875696]
MF20='out1mf20':'constant',[583.74432489796]
MF21='out1mf21':'constant',[-426.720072618589]
```

```
MF22='out1mf22':'constant',[243.98901637816]
MF23='out1mf23':'constant',[245.157829022137]
MF24='out1mf24':'constant',[273.766356275393]
MF25='out1mf25':'constant',[653.503853229221]
MF26='out1mf26':'constant',[318.91160416392]
MF27='out1mf27':'constant',[264.905677701838]

[Rules]
1 1 1, 1 (1) : 1
1 1 2, 2 (1) : 1
1 1 3, 3 (1) : 1
1 2 1, 4 (1) : 1
1 2 2, 5 (1) : 1
1 2 3, 6 (1) : 1
1 3 1, 7 (1) : 1
1 3 2, 8 (1) : 1
1 3 3, 9 (1) : 1
2 1 1, 10 (1) : 1
2 1 2, 11 (1) : 1
2 1 3, 12 (1) : 1
2 2 1, 13 (1) : 1
2 2 2, 14 (1) : 1
2 2 3, 15 (1) : 1
2 3 1, 16 (1) : 1
2 3 2, 17 (1) : 1
2 3 3, 18 (1) : 1
3 1 1, 19 (1) : 1
3 1 2, 20 (1) : 1
3 1 3, 21 (1) : 1
3 2 1, 22 (1) : 1
3 2 2, 23 (1) : 1
3 2 3, 24 (1) : 1
3 3 1, 25 (1) : 1
3 3 2, 26 (1) : 1
3 3 3, 27 (1) : 1
```

Code for efficiency for 1/LP/E configuration

```
[System]
Name='1LPE_eff'
Type='sugeno'
Version=2.0
NumInputs=4
NumOutputs=1
NumRules=81
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='cr'
Range=[1.8181 2.5965]
Constraintfun1lpeef
```

```
NumMFs=3
MF1='in1mf1':'trimf',[1.42890000003743 1.81854861657353 2.20646371546276]
MF2='in1mf2':'trimf',[1.81771612912804 2.20758051333137 2.59649805335471]
MF3='in1mf3':'trimf',[2.20326230880453 2.59633347106627 2.9857]

[Input2]
Name='rr'
Range=[1.1134 1.8621]
NumMFs=3
MF1='in2mf1':'trimf',[0.739050000045261 1.1137387696775 1.48773385874276]
MF2='in2mf2':'trimf',[1.11313657376466 1.48830072815751 1.86213362929506]
MF3='in2mf3':'trimf',[1.48394074132629 1.86231130910654 2.23645]

[Input3]
Name='hpr'
Range=[0.7111 0.8612]
NumMFs=3
MF1='in3mf1':'trimf',[0.63605 0.711281761927735 0.778751513896651]
MF2='in3mf2':'trimf',[0.711441648939249 0.782824860927289 0.863323470860997]
MF3='in3mf3':'trimf',[0.777086107745971 0.858742958090317 0.936249985409906]

[Input4]
Name='lpr'
Range=[0.7035 0.7752]
NumMFs=3
MF1='in4mf1':'trimf',[0.667650065787791 0.704457427090265 0.749459853172237]
MF2='in4mf2':'trimf',[0.702912888883434 0.751869273986898 0.770379623975249]
MF3='in4mf3':'trimf',[0.753525564975656 0.784493750625753 0.81105]

[Output1]
Name='effi'
Range=[0.2637 0.935]
NumMFs=81
MF1='out1mf1':'constant',[1.50586752564541]
MF2='out1mf2':'constant',[0.0655037603218385]
MF3='out1mf3':'constant',[7.44527433366251]
MF4='out1mf4':'constant',[0.273169458194899]
MF5='out1mf5':'constant',[0.308808148509368]
MF6='out1mf6':'constant',[-1.2743543798848]
MF7='out1mf7':'constant',[0.603697800963218]
MF8='out1mf8':'constant',[0.383644933402358]
MF9='out1mf9':'constant',[4.82109191231669]
MF10='out1mf10':'constant',[0.0186436548979009]
MF11='out1mf11':'constant',[0.472750849884553]
MF12='out1mf12':'constant',[-0.827465020118969]
MF13='out1mf13':'constant',[0.517916246322918]
MF14='out1mf14':'constant',[0.399529301063951]
MF15='out1mf15':'constant',[0.781765526869769]
MF16='out1mf16':'constant',[0.485293033827036]
MF17='out1mf17':'constant',[0.416219574252491]
MF18='out1mf18':'constant',[-0.597822518007879]
MF19='out1mf19':'constant',[1.78521479791139]
MF20='out1mf20':'constant',[0.362233058199344]
MF21='out1mf21':'constant',[-0.0953611029742665]
MF22='out1mf22':'constant',[0.455626796307567]
MF23='out1mf23':'constant',[0.522679257239759]
```

```
MF24='out1mf24':'constant',[1.06360585488616]
MF25='out1mf25':'constant',[0.817974141376303]
MF26='out1mf26':'constant',[0.815437771189773]
MF27='out1mf27':'constant',[5.09129166421679]
MF28='out1mf28':'constant',[-0.068286386783879]
MF29='out1mf29':'constant',[0.445265681600613]
MF30='out1mf30':'constant',[-8.87250550550197]
MF31='out1mf31':'constant',[0.45000847360349]
MF32='out1mf32':'constant',[0.379000526409853]
MF33='out1mf33':'constant',[2.66450606671076]
MF34='out1mf34':'constant',[0.461441108215117]
MF35='out1mf35':'constant',[0.268448178317799]
MF36='out1mf36':'constant',[-6.03057923477316]
MF37='out1mf37':'constant',[0.777804504566508]
MF38='out1mf38':'constant',[0.382882717102945]
MF39='out1mf39':'constant',[2.47773838614831]
MF40='out1mf40':'constant',[0.611153745257727]
MF41='out1mf41':'constant',[0.552331145751217]
MF42='out1mf42':'constant',[-0.0871226517652191]
MF43='out1mf43':'constant',[0.730209352246175]
MF44='out1mf44':'constant',[0.610777693348569]
MF45='out1mf45':'constant',[2.43125653414702]
MF46='out1mf46':'constant',[1.49167110626961]
MF47='out1mf47':'constant',[0.24436339154329]
MF48='out1mf48':'constant',[-0.327485169772646]
MF49='out1mf49':'constant',[1.03712719758291]
MF50='out1mf50':'constant',[1.09655260882817]
MF51='out1mf51':'constant',[-1.0640280861982]
MF52='out1mf52':'constant',[1.3854777129522]
MF53='out1mf53':'constant',[0.347497502339099]
MF54='out1mf54':'constant',[3.5274036059553]
MF55='out1mf55':'constant',[2.18853585217357]
MF56='out1mf56':'constant',[0.833719532631766]
MF57='out1mf57':'constant',[0]
MF58='out1mf58':'constant',[-0.663022506340248]
MF59='out1mf59':'constant',[1.46436215332138]
MF60='out1mf60':'constant',[-0.285054502033911]
MF61='out1mf61':'constant',[0.291288833202481]
MF62='out1mf62':'constant',[5.61482269792216]
MF63='out1mf63':'constant',[-0.391701132280546]
MF64='out1mf64':'constant',[-0.470232127112797]
MF65='out1mf65':'constant',[3.28853597619268]
MF66='out1mf66':'constant',[-0.223043412449418]
MF67='out1mf67':'constant',[1.92076214224365]
MF68='out1mf68':'constant',[-0.915134016716002]
MF69='out1mf69':'constant',[6.18637810238212]
MF70='out1mf70':'constant',[1.05942780345651]
MF71='out1mf71':'constant',[-4.74642798237645]
MF72='out1mf72':'constant',[-5.20251231946648]
MF73='out1mf73':'constant',[0]
MF74='out1mf74':'constant',[-5.13942587364315]
MF75='out1mf75':'constant',[-0.0627856953884867]
MF76='out1mf76':'constant',[4.57446867714398]
MF77='out1mf77':'constant',[4.65796626510757]
MF78='out1mf78':'constant',[2.1613540274228]
MF79='out1mf79':'constant',[0.713081509078347]
MF80='out1mf80':'constant',[12.9318353668161]
```

```
MF81='out1mf81':'constant',[0.415589583587l5]

[Rules]
1 1 1 1, 1 (1) : 1
1 1 1 2, 2 (1) : 1
1 1 1 3, 3 (1) : 1
1 1 2 1, 4 (1) : 1
1 1 2 2, 5 (1) : 1
1 1 2 3, 6 (1) : 1
1 1 3 1, 7 (1) : 1
1 1 3 2, 8 (1) : 1
1 1 3 3, 9 (1) : 1
1 2 1 1, 10 (1) : 1
1 2 1 2, 11 (1) : 1
1 2 1 3, 12 (1) : 1
1 2 2 1, 13 (1) : 1
1 2 2 2, 14 (1) : 1
1 2 2 3, 15 (1) : 1
1 2 3 1, 16 (1) : 1
1 2 3 2, 17 (1) : 1
1 2 3 3, 18 (1) : 1
1 3 1 1, 19 (1) : 1
1 3 1 2, 20 (1) : 1
1 3 1 3, 21 (1) : 1
1 3 2 1, 22 (1) : 1
1 3 2 2, 23 (1) : 1
1 3 2 3, 24 (1) : 1
1 3 3 1, 25 (1) : 1
1 3 3 2, 26 (1) : 1
1 3 3 3, 27 (1) : 1
2 1 1 1, 28 (1) : 1
2 1 1 2, 29 (1) : 1
2 1 1 3, 30 (1) : 1
2 1 2 1, 31 (1) : 1
2 1 2 2, 32 (1) : 1
2 1 2 3, 33 (1) : 1
2 1 3 1, 34 (1) : 1
2 1 3 2, 35 (1) : 1
2 1 3 3, 36 (1) : 1
2 2 1 1, 37 (1) : 1
2 2 1 2, 38 (1) : 1
2 2 1 3, 39 (1) : 1
2 2 2 1, 40 (1) : 1
2 2 2 2, 41 (1) : 1
2 2 2 3, 42 (1) : 1
2 2 3 1, 43 (1) : 1
2 2 3 2, 44 (1) : 1
2 2 3 3, 45 (1) : 1
2 3 1 1, 46 (1) : 1
2 3 1 2, 47 (1) : 1
2 3 1 3, 48 (1) : 1
2 3 2 1, 49 (1) : 1
2 3 2 2, 50 (1) : 1
2 3 2 3, 51 (1) : 1
2 3 3 1, 52 (1) : 1
2 3 3 2, 53 (1) : 1
2 3 3 3, 54 (1) : 1
```

```
3 1 1 1, 55 (1) : 1
3 1 1 2, 56 (1) : 1
3 1 1 3, 57 (1) : 1
3 1 2 1, 58 (1) : 1
3 1 2 2, 59 (1) : 1
3 1 2 3, 60 (1) : 1
3 1 3 1, 61 (1) : 1
3 1 3 2, 62 (1) : 1
3 1 3 3, 63 (1) : 1
3 2 1 1, 64 (1) : 1
3 2 1 2, 65 (1) : 1
3 2 1 3, 66 (1) : 1
3 2 2 1, 67 (1) : 1
3 2 2 2, 68 (1) : 1
3 2 2 3, 69 (1) : 1
3 2 3 1, 70 (1) : 1
3 2 3 2, 71 (1) : 1
3 2 3 3, 72 (1) : 1
3 3 1 1, 73 (1) : 1
3 3 1 2, 74 (1) : 1
3 3 1 3, 75 (1) : 1
3 3 2 1, 76 (1) : 1
3 3 2 2, 77 (1) : 1
3 3 2 3, 78 (1) : 1
3 3 3 1, 79 (1) : 1
3 3 3 2, 80 (1) : 1
3 3 3 3, 81 (1) : 1
```

Code for specific work done for 1/LP/E configuration

```
[System]
Name='1LPE_swd'
Type='sugeno'
Version=2.0
NumInputs=4
NumOutputs=1
NumRules=81
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='cr'
Range=[1.8181 2.5965]
Constraintfun1lpeswd
NumMFs=3
MF1='in1mf1':'trimf',[1.4289 1.81812246365821 2.20725522932233]
MF2='in1mf2':'trimf',[1.81810445429738 2.20730384434647 2.59649759974479]
MF3='in1mf3':'trimf',[2.20710669458874 2.59648138068826 2.9857]

[Input2]
Name='rr'
Range=[1.1134 1.8621]
```

```
NumMFs=3
MF1='in2mf1':'trimf',[0.73905 1.1133321319745 1.48792591730063]
MF2='in2mf2':'trimf',[1.11348687967321 1.48764469153223 1.86210116603057]
MF3='in2mf3':'trimf',[1.48780587862029 1.86206255955773 2.23645]

[Input3]
Name='hpr'
Range=[0.7111 0.8937]
NumMFs=3
MF1='in3mf1':'trimf',[0.6198 0.711295754825707 0.805149591298436]
MF2='in3mf2':'trimf',[0.710942798965276 0.802521528381954 0.893646774518123]
MF3='in3mf3':'trimf',[0.801764126376008 0.893625773556248 0.985]

[Input4]
Name='lpr'
Range=[0.7035 0.7752]
NumMFs=3
MF1='in4mf1':'trimf',[0.66765 0.704053905119215 0.746337905604375]
MF2='in4mf2':'trimf',[0.703085614506909 0.739830637925824 0.774763400018387]
MF3='in4mf3':'trimf',[0.732860474771222 0.775126732806609 0.81105]

[Output1]
Name='swd'
Range=[266.92 389.77]
NumMFs=81
MF1='out1mf1':'constant',[317.9104296936]
MF2='out1mf2':'constant',[250.729360397145]
MF3='out1mf3':'constant',[323.99176651457]
MF4='out1mf4':'constant',[568.724594904877]
MF5='out1mf5':'constant',[367.364957899333]
MF6='out1mf6':'constant',[243.579396879647]
MF7='out1mf7':'constant',[-1565.75160519833]
MF8='out1mf8':'constant',[823.35659333478]
MF9='out1mf9':'constant',[-136.209914253541]
MF10='out1mf10':'constant',[140.427302079797]
MF11='out1mf11':'constant',[366.164846530742]
MF12='out1mf12':'constant',[156.805959159206]
MF13='out1mf13':'constant',[410.605073297267]
MF14='out1mf14':'constant',[294.44149162122]
MF15='out1mf15':'constant',[351.885803512318]
MF16='out1mf16':'constant',[141.532034599849]
MF17='out1mf17':'constant',[520.001613878571]
MF18='out1mf18':'constant',[56.8984446835147]
MF19='out1mf19':'constant',[628.752560205117]
MF20='out1mf20':'constant',[192.521053406624]
MF21='out1mf21':'constant',[439.551212294902]
MF22='out1mf22':'constant',[343.919541671399]
MF23='out1mf23':'constant',[404.681055838922]
MF24='out1mf24':'constant',[160.613441505022]
MF25='out1mf25':'constant',[1630.0691926811]
MF26='out1mf26':'constant',[-277.521946594976]
MF27='out1mf27':'constant',[2177.74780427269]
MF28='out1mf28':'constant',[352.361149607555]
MF29='out1mf29':'constant',[274.022587271253]
MF30='out1mf30':'constant',[337.059954163238]
MF31='out1mf31':'constant',[337.743185096296]
```

```
MF32='out1mf32':'constant',[358.100164396079]
MF33='out1mf33':'constant',[226.077390646705]
MF34='out1mf34':'constant',[664.661809245881]
MF35='out1mf35':'constant',[47.8567595005767]
MF36='out1mf36':'constant',[766.70778007855]
MF37='out1mf37':'constant',[283.416995711161]
MF38='out1mf38':'constant',[329.679707424149]
MF39='out1mf39':'constant',[174.233594665779]
MF40='out1mf40':'constant',[397.196158354278]
MF41='out1mf41':'constant',[329.436386482385]
MF42='out1mf42':'constant',[329.275514559057]
MF43='out1mf43':'constant',[479.842268225516]
MF44='out1mf44':'constant',[379.90894323881]
MF45='out1mf45':'constant',[278.869122337404]
MF46='out1mf46':'constant',[405.95487835803]
MF47='out1mf47':'constant',[226.969419576423]
MF48='out1mf48':'constant',[629.766789041869]
MF49='out1mf49':'constant',[343.66777912949]
MF50='out1mf50':'constant',[320.748387375618]
MF51='out1mf51':'constant',[213.557808212667]
MF52='out1mf52':'constant',[-15.3288007340792]
MF53='out1mf53':'constant',[446.983857541554]
MF54='out1mf54':'constant',[614.12895299559]
MF55='out1mf55':'constant',[495.845920959395]
MF56='out1mf56':'constant',[160.36613459315]
MF57='out1mf57':'constant',[-323.53790457178]
MF58='out1mf58':'constant',[-53.5913127733951]
MF59='out1mf59':'constant',[601.281169467294]
MF60='out1mf60':'constant',[238.261720291183]
MF61='out1mf61':'constant',[0]
MF62='out1mf62':'constant',[115.023150815409]
MF63='out1mf63':'constant',[362.083242039621]
MF64='out1mf64':'constant',[641.38496948764]
MF65='out1mf65':'constant',[250.192768155216]
MF66='out1mf66':'constant',[492.204761851769]
MF67='out1mf67':'constant',[326.745462100518]
MF68='out1mf68':'constant',[314.910565901936]
MF69='out1mf69':'constant',[351.653230656812]
MF70='out1mf70':'constant',[1277.67713902468]
MF71='out1mf71':'constant',[-1243.523670855]
MF72='out1mf72':'constant',[500.755394547026]
MF73='out1mf73':'constant',[6.32149919638671]
MF74='out1mf74':'constant',[121.412779629294]
MF75='out1mf75':'constant',[159.937721864003]
MF76='out1mf76':'constant',[1545.13710500474]
MF77='out1mf77':'constant',[802.749709454705]
MF78='out1mf78':'constant',[-605.625866332446]
MF79='out1mf79':'constant',[404.06648146328]
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