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Design of Fuzzy Energy and Reserve Co-Optimization Hardware-In-Loop with High Penetration of Renewable Energy

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ABSTRACT: Renewable energy resources have been rapidly integrated into power systems in many parts of the world, contributing to a cleaner and a more sustainable supply of electricity. During high penetration of renewable energy combine Adaptive Neuro Fuzzy Inference System and Particle Swam Optimization technique and propose a joint energy and reserve scheduling model that considers robust re-dispatches with renewable uncertainties as well as soft boundaries of uncertainty sets. The high penetrated wind power is given as input to the ANFIS system. Convert crisp data of input power that to fuzzy values using the fuzzy membership functions. Evaluate the rules and data base in the inference system. This gives ANFIS output power for each wind system. To convert the fuzzy values of output power into crisp values defuzzification is performed. To get the optimized value of wind power from the fuzzy membership functions, Particle Swam Optimization technique is used in defuzzification process. The optimization model calculates efficient schedules by considering trade-off between the system operating risk and economic scheduling cost. The optimized power is applied to the IEEE 118-bus power system to verify the effectiveness of the model.

I. INTRODUCTION

Renewable energy is energy that is collected from renewable resources, which are naturally replenished on a human timescale, such as sunlight, wind, rain, tides, waves, and geothermal heat. Renewable energy often provides energy in four important areas: electricity generation, air and water heating/cooling, transportation, and rural (off-grid) energy services.

Renewable energy is derived from natural processes that are replenished constantly. In its various forms, it derives directly from the sun, or from heat generated deep within the earth. Included in the definition is electricity and heat generated from solar, wind, ocean, hydropower, biomass, geothermal resources, and biofuels and hydrogen derived from renewable resources.

Renewable energy resources exist over wide geographical areas, in contrast to other energy sources, which are concentrated in a limited number of countries. Rapid deployment of renewable energy and energy efficiency is resulting in significant energy security, climate change mitigation, and economic benefits. The results of a recent review of the literature concluded that as greenhouse gas (GHG) emitters begin to be held liable for damages resulting from GHG emissions resulting in climate change, a high value for liability mitigation would provide powerful incentives for deployment of renewable energy technologies. In international public opinion surveys there is strong support for promoting renewable sources such as solar power and wind power. At the national level, at least 30 nations around the world already have renewable energy contributing more than 20 percent of energy supply. National renewable energy markets are projected to continue to grow strongly in the coming decade and beyond. Some places

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and at least two countries, Iceland and Norway generate all their electricity using renewable energy already, and many other countries have the set a goal to reach 100% renewable energy in the future.

Wind power, a renewable and virtually inexhaustible power source, is a promising means of green energy production. Currently, wind power is not in wide use and accounts for the production of only 1% of energy used world-wide. The wind power industry has experienced continued growth in the past year.

Wind power is basically converted solar power. As the sun heats the earth, land masses and oceans, are heated in varying degrees as they absorb and reflect heat at different rates. This causes portions of the atmosphere to warm differently and as hot air rises, atmospheric pressure causes cooler air to replace it. The resulting movement in the air is wind.

The kinetic energy of wind is converted by turbine blades which drive a generator to produce electrical energy. Wind power can be harnessed using wind turbines grouped together on wind farms, located either on land or offshore, for large-scale production. Wind power generation varies in size from small generators which produce sufficient electrical power for a small farm to wind farms which can generate power for thousands of households.

The intermittent nature of wind makes reliability and storage of wind energy an important issue. Utilities must maintain sufficient power to meet customer demand plus an additional reserve margin. Although wind is variable and at times does not blow at all, fluctuations in the output from wind farms can be accommodated within normal operating strategies, as the majority of wind is added to power systems as an energy source rather than a capacity source. A spinning reserve enables a plant to meet demand. Amount of energy production is based on how average wind speed at the site of the wind farm and the correlation between output and demand. Capacity of wind farms also depends on geographical dispersion-the farther apart wind plants are located, the greater the chance that some of them will be producing power at any given time.

The capacity of the transmission grid to deliver wind energy to customers has been identified as one of the biggest constraints on wind energy use in the U.S. Often areas of high wind which are best suited as sites or wind farms are not located near demand centers, causing the power generated to be transmitted over long distances resulting in loss of power. Costs are also increased with the necessity of building transmission lines and substations.

Environmental concern has been raised over avian fatalities caused by collisions with wind turbines. Bird deaths caused by wind turbines are low compared to avian death caused by birds flying into buildings and windows, but environmentalists urge that patterns of bird flight and paths of migration should factor into site selection for wind farms.

Wind power is the fastest growing power source worldwide on a percentage basis and according to the U.S. Department of Energy global winds could theoretically supply more than 15 times current world energy demand.

II. RELATED WORK

F. Qiu, Jianhui Wang , et al., [1] propose a distributionally robust congestion management model that selectively uses dynamic ratings on critical lines and keeps the risk of thermal overloading below a prescribed level. A case study illustrates that the proposed model can effectively alleviate transmission congestion with a low error rate.

Q. Bian, and K. P. Wong, et al., [2] present a distributionally robust optimization (DRO) model is presented for the reserve schedule decision-making problem with partial information of wind power, aiming to find a robust solution to the uncertainty of wind power probability distribution. The stochastic problem can be converted into an equivalent deterministic bilinear matrix inequality (BMI) problem.

C.Liu, and H. Chen et al., [3] presents a stochastic robust framework for two-stage power system optimization problems with uncertainty. The model optimizes the probabilistic expectation of different worst-case scenarios with different uncertainty sets.

B. Wang, et al., [4] develops a day-ahead two-stage multi-objective unit commitment model which optimizes both the supply reliability and the total cost with environmental concerns of thermal generation systems. To tackle the manifold uncertainties of unit commitment in a more comprehensive and realistic manner, stochastic and fuzzy set theories are utilized simultaneously, and a unified reliability measurement is then introduced to evaluate the system reliability under the uncertainties of both sudden unit outage and unforeseen load fluctuation.

M. Shahidehpour et al., [5] compares applications of scenario-based and interval optimization approaches to stochastic security-constrained unit commitment (Stochastic SCUC). The uncertainty of wind power generation is considered in this study to compare the two approaches, while other types of uncertainty can be addressed similarly. For the simulation of uncertainty, the scenario-based approach considers the Monte Carlo (MC) method, while lower and upper bounds are adopted in the interval optimization. The Stochastic SCUC problem is formulated as a mixed-integer linear programming (MIP) problem and solved using the two approaches. The scenario-based solutions are insensitive to the number of scenarios, but present additional computation burdens.

III. SYSTEM IMPLEMENTATION

A) INTRODUCTION

Renewable energy resources have been rapidly integrated into power systems in many parts of the world, contributing to a cleaner and more sustainable supply of electricity. Wind and solar resources also introduce new challenges for system operations and planning in terms of economics and reliability due to their variability and uncertainty. At the heart of the challenge is to efficiently address the uncertainty and variability of the renewable resources in operational decisions that focus on unit commitment (UC) and economic dispatch (ED) methods from day-ahead scheduling to real-time operations.

Fuzzy theory has been used for dealing with power system operation problems for more than two decades. In, a fuzzy model for power system operation is presented, where uncertainties in load and generation are modeled as fuzzy numbers. System behavior under inexact (while uncertain) injections is dealt with by a DC fuzzy power flow model. In, an optimal power flow (OPF) formulation that can handle fuzzy constraints is presented. The proposed method converts the fuzzy OPF problem into a crisp optimization problem and solves this problem by using an iterative linear programming technique. Reference presents a mathematical formulation for the optimal reactive power control problem using the fuzzy set theory. The objective function and the constraints are modeled by fuzzy sets. Paper presents a new multi objective Tabu search algorithm to solve a multi objective fuzzy model for optimal planning of distribution systems. In, an approach to the fuzzy UC problem using the absolutely stochastic simulated annealing method is proposed. Paper presents a new fuzzy-optimization-based approach to solving the thermal UC problem. In this approach, load demand, reserve requirements, and scheduling cost are expressed by fuzzy set notations, while unit generation limits, ramp rate limits, and minimum up and/or down limits are handled as crisp constraints.

Project presents a UC formulation considering both renewable integration and emissions requirements. The reliability and emission constraints are modeled as fuzzy constraints. The model is solved by using simulated annealing. Reference presents two approaches for addressing wind power forecast uncertainty in the day-ahead UC. The first approach uses a fuzzy objective function that considers expected energy not served and total operating costs, whereas the second approach increases operating reserves in a deterministic UC. Reference presents a UC model considering demand response of electric vehicles as well as wind power. To deal with the UC problem, the authors use a fuzzy chance-constrained program that takes into account the wind power forecasting errors. Proposes a one stage UC solution to minimize cost as well as risk. Integration of wind power introduces uncertainty in the solution that may be quantified through an imbalance risk function. The total cost and risk are modeled by using fuzzy sets. Reference uses probability theory to model the unit outage rate and applies fuzzy set theory to describe the load uncertainty, then the UC problem in this study is established as an optimization problem under stochastic and fuzzy uncertainties. A multi-objective optimization considering minimum cost as well as reliability measurement is proposed to obtain the power system schedule.

B) PROPOSED SYSTEM

Traditionally, the spinning and non-spinning reserve requirement is based on a probabilistic or deterministic representation of contingencies. However, in the environment of high penetration of renewables, the scheduled energy and operating reserves should also be dependent on the uncertainty in renewables. In two-stage security-constrained UC or economic dispatch problems, considering a larger uncertainty set of renewables in general leads to a smaller operating risk, e.g. measured in terms of the likelihood of lost load or reserve shortages. If there is potential generation shortage caused by overestimation of renewables, the system operator has to buy an additional amount of reserve in advance, to cover a potential supply-demand gap. Furthermore, it is difficult to describe tail events accurately and to

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determine the exact boundary of the considered uncertainty set in probabilistic terms. Therefore, fuzzy theory is an ideal alternative concept to model the likeness of the soft boundaries of uncertainty sets.
In this project, we propose a fuzzy based energy and reserve co-optimization scheduling model. The main contributions of the paper include:
1) We combine fuzzy theory and two-stage robust interval optimization and propose a joint energy and reserve scheduling model that considers robust re-dispatches with renewable uncertainties as well as the soft boundaries of uncertainty sets.
2) The lower bound of the uncertainty set is expressed as fuzzy membership functions. The proposed model provides adequate scheduling solution in the occurrence of incomplete or vague information about uncertain factors.
3) The optimization model calculates efficient schedules by considering the trade-off between the system operating risk and economic scheduling cost.

C) RESERVE CO-OPTIMIZATION WITH HIGH PENETRATION

(i) Two-stage mathematical programming model

A two-stage co-optimization model is proposed to address the uncertainty in wind power output. The structures and philosophy in the two stages are different respectively. The first-stage problem corresponds directly to current decision-making, before future uncertainties are disclosed. Once the decisions in the first stage are made, they cannot be changed in the second stage. The second-stage problem considers the recourse cost and examines the viability of the decisions made in the first stage using scenarios.
In two stage Energy and Reserve co-optimization problem, the first stage of the problem corresponds directly to day-ahead energy and reserve clearing and unit commitment which will be kept in real time (second stage). The second-stage problem considers the real-time generation re-dispatch and correction which is based on the actual wind power output and the unit commitment, energy and reserve solution from the first stage. Hence, in our model, the decision variables in the first stage are the commitment status, cleared reserve of all thermal generating units considering the decision variables including generation correction, re-dispatch and wind power output in the second stage.
The multi-period security-constrained Interval UC and energy and reserve co-dispatch can be formulated as (1). The objective function is to minimize the sum of the UC cost, energy cost, reserve cost and unserved energy and reserve cost for the expected wind power level. It represent UC constraints, power balance constraints, wind constraints, reserve requirement constraints, relationship of scheduled power, reserve and maximum and/or minimum capacity, relationship of reserve and ramp rate, ramping constraints, and transmission limits constraints, respectively. The constraint on minimal spinning reserve requirement for the system is related to the dispatch levels of all thermal generating units (N-1 criterion). The spinning reserve is also implicitly determined by transition distance limits between the base case scenario and all other possible scenarios. The operating reserve requirement in Constraint can be determined by the highest generator capacity and a percentage of the total load. In this paper, we assume that all reserves are provided by thermal units, and that wind and demand does not provide reserves. The renewable uncertainty set is modeled as an interval $[\underline{W}_{i,,}]$ in constraint . Constraints represent the transition distance limits between the base case wind power scenario and all other possible scenarios. In each possible scenario, corrective actions are considered based on $P_{i,}-P_{i,t}\leq SR_{i,t}$ for mitigating the deviations in renewable energy. The physically acceptable adjustments of non-wind generating units will be less than cleared spinning reserves to accommodate the volatility of wind. Corrective actions refer to the redispatch of non-wind units while satisfying power flow imbalances and transmission network violations in real time. It denotes system load balance of each scenario. Constraint represents transmission constraints for all possible scenarios within the wind power interval. Renewable power can be dispatched down to below its maximal available energy.

$$Min \sum_{i\epsilon G} \sum_{t\epsilon T} \left(Csu_i . Y_{i,t} + Csd_i . Z_{i,t} + Cf_i . I_{i,t} + Ce_{i,t} . P_{i,t} + CSR_{i,t} . SR_{i,t} + Cnsr_{i,t} . NSR_{i,t} \right) + \sum_{t\epsilon T} (Cen_t . LN_t + Csrn_t . SRN_t + Cnsrn_t . NSRN_t) \qquad \_\_\_\_ (1)$$

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(ii) Adaptive Neuro Fuzzy Inference System

An adaptive Neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The technique was developed in the early 1990s. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator. For using the ANFIS in a more efficient and optimal way, one can use the best parameters obtained by genetic algorithm
The adaptive network-based fuzzy inference systems (ANFIS) is used to solve problems related to parameter identification. This parameter identification is done through a hybrid learning rule combining the back-propagation gradient descent and a least-squares method.

ANFIS is basically a *graphical* network representation of Sugeno-type fuzzy systems endowed with the neural learning capabilities. The network is comprised of nodes with specific functions collected in layers. ANFIS is able to construct a network realization of IF / THEN rules.

Consider a Sugeno type of fuzzy system having the rule base

1. If x is $A1$and y is $B1$, then $f_1= c_{11}x+c_{12}y+c_{10}$

2. If x is $A2$and y is $B2$, then $f_2= c_{21}x+c_{22}y+c_{20}$

Let the membership functions of fuzzy sets Ai, Bi, i=1,2, be , $\mu_{Ai}\mu_{Bi}$.

In evaluating the rules, choose *product* for T-norm (logical *and*).

1. Evaluating the rule premises results in

$$w_i = \mu_{A_i}(x)\mu_{B_i}(y),\ i=1,2.$$

2. Evaluating the implication and the rule consequences gives

$$f(x,y) = \frac{w_1(x,y)f_1(x,y)+w_2(x,y)f_2(x,y)}{w_1(x,y)+w_2(x,y)}.$$

Or leaving the arguments out

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2}$$

This can be separated to phases by first defining

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}$$

Then f can be written as

$$f = \overline{w}_1 f_1 + \overline{w}_2 f_2$$

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All computations can be presented in a diagram form. ANFIS normally has 5 layers of neurons of which neurons in the same layer are of the same function family.

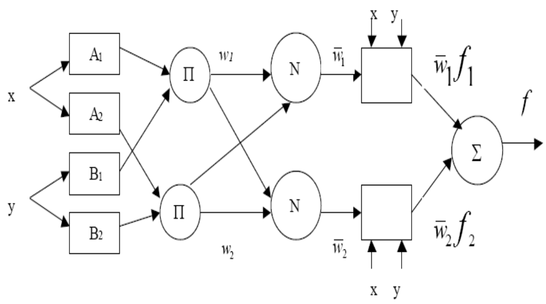

Figure 1: Structure of the ANFIS network.

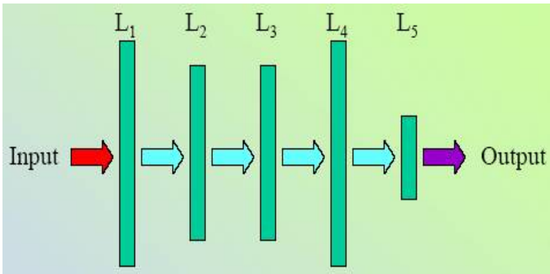

Figure 2: ANFIS Architecture

Layer 1 (L1): Each node generates the membership grades of a linguistic label.

An example of a membership function is the generalised *bell function*:

$$\mu(x) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}}$$

Where $\{a, b, c\}$ is the parameter set. As the values of the parameters change, the shape of the bell-shaped function varies. Parameters in that layer are called *premise parameters*.

Layer 2 (L2): Each node calculates the firing strength of each rule using the *min* or *prod* operator. In general, any other fuzzy AND operation can be used.

Layer 3 (L3): The nodes calculate the ratios of the rule's firing strength to the sum of all the rules firing strength. The result is a *normalized firing strength*.

Layer 4 (L4): The nodes compute a parameter function on the layer 3 output. Parameters in this layer are called *consequent parameters*.

Layer 5 (L5): Normally a single node that aggregates the overall output as the summation of all incoming signals

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(iii) The ANFIS learning algorithm

When the premise parameters are fixed, the overall output is a linear combination of the consequent parameters. In symbols, the output f can be written as

$$f = (\bar{w}_1 x) c_{11} + (\bar{w}_1 y) c_{12} + \bar{w}_1 c_{10} + (\bar{w}_2 x) c_{21} + (\bar{w}_2 y) c_{22} + \bar{w}_2 c_{20}$$

Which is linear in the consequent parameters c_{ij} ($i = 1,2$, $j = 0,1,2$). A hybrid algorithm adjusts the consequent parameters c_{ij} in a forward pass and the premise parameters $\{a_i, b_i, c_i\}$ in a backward pass (Jang et al., 1997). In the forward pass the network inputs propagate forward until layer 4, where the consequent parameters are identified by the least-squares method. In the backward pass, the error signals propagate backwards and the premise parameters are updated by gradient descent.

Because the update rules for the premise and consequent parameters are decoupled in the hybrid learning rule, a computational speedup may be possible by using variants of the gradient method or other optimisation techniques on the premise parameters.

D) PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization is an approach to problems whose solutions can be represented as a point in an n-dimensional solution space. A number of particles are randomly set into motion through this space. At each iteration, they observe the "fitness" of themselves and their neighbours and "emulate" successful neighbours (those whose current position represents a better solution to the problem than theirs) by moving towards them. Various schemes for grouping particles into competing, semi-independent *flocks* can be used, or all the particles can belong to a single global flock. This extremely simple approach has been surprisingly effective across a variety of problem domains.

1. The PSO algorithm

As stated before, PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. So what's the best strategy to find the food? The effective one is to follow the bird which is nearest to the food.

PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest.

After finding the two best values, the particle updates its velocity and positions with following equation (a) and (b).

v[] = v[] + c1 * rand() * (pbest[] - present[]) + c2 * rand() * (gbest[] - present[]) (a)

present[] = present[] + v[] (b)

v[] is the particle velocity, present[] is the current particle (solution). pbest[] and gbest[] are defined as stated before. rand () is a random number between (0,1). c1, c2 are learning factors. usually c1 = c2 = 2.

Particles' velocities on each dimension are clamped to a maximum velocity Vmax. If the sum of accelerations would cause the velocity on that dimension to exceed Vmax, which is a parameter specified by the user. Then the velocity on that dimension is limited to Vmax.

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2. PSO parameter control

From the above case, we can learn that there are two key steps when applying PSO to optimization problems: the representation of the solution and the fitness function. One of the advantages of PSO is that PSO take real numbers as particles. It is not like GA, which needs to change to binary encoding, or special genetic operators have to be used. For example, we try to find the solution for f(x) = x1^2 + x2^2+x3^2, the particle can be set as (x1, x2, x3), and fitness function is f(x). Then we can use the standard procedure to find the optimum. The searching is a repeat process, and the stop criteria are that the maximum iteration number is reached or the minimum error condition is satisfied.
There are not many parameter need to be tuned in PSO. Here is a list of the parameters and their typical values.

The number of particles: the typical range is 20 - 40. Actually for most of the problems 10 particles is large enough to get good results. For some difficult or special problems, one can try 100 or 200 particles as well.

Dimension of particles: It is determined by the problem to be optimized,
Range of particles: It is also determined by the problem to be optimized, you can specify different ranges for different dimension of particles.

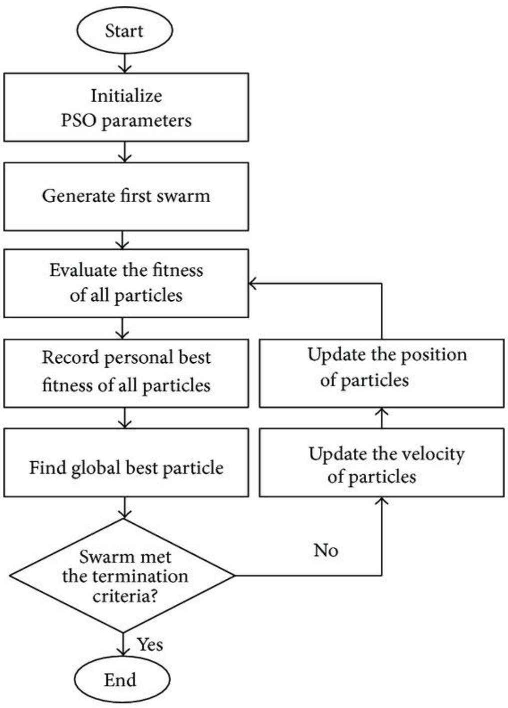
Vmax: it determines the maximum change one particle can take during one iteration. Usually we set the range of the particle as the Vmax for example, the particle (x1, x2, x3)

X1 belongs [-10, 10], then Vmax = 20.

Learning factors: c1 and c2 usually equal to 2. However, other settings were also used in different papers. But usually c1 equals to c2 and ranges from [0, 4]

The stop condition: the maximum number of iterations the PSO execute and the minimum error requirement

3. Flow chart of PSO



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IV. RESULTS AND CONCLUSION

A) SIMULATION RESULTS

It ensures the image processing steps used are completely documented, and hence can be replicated.
In general, the source code for all image processing functions are accessible for scrutiny and test.
It allows one to ensure numerical precision is maintained all the way through the enhancement process.
Image processing algorithms available under MATLAB are likely to be more advanced than those available from other image processing applications.

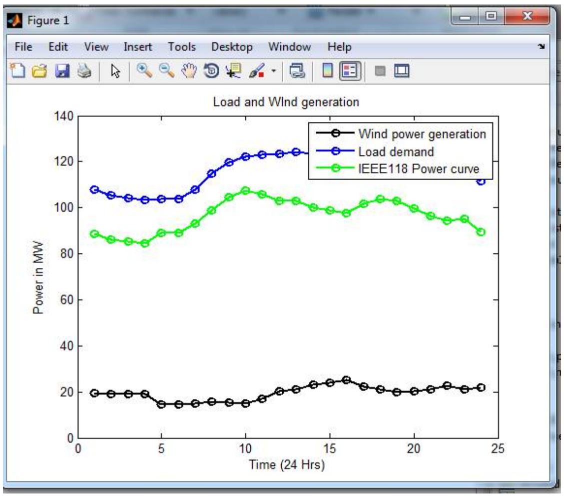

Fig 4.1 Load data

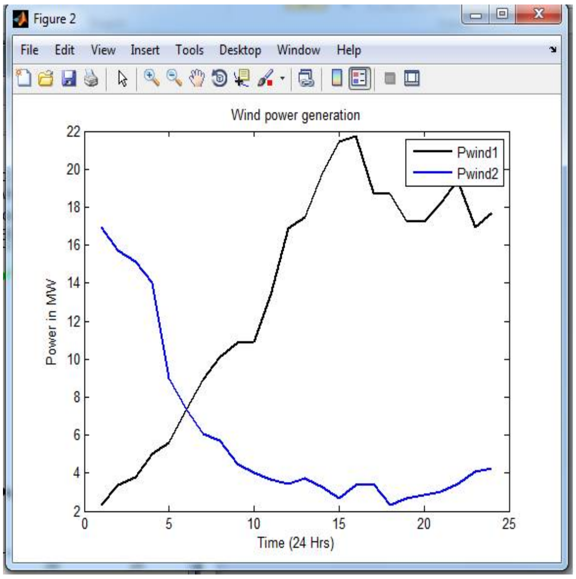

Fig 4.2 Comparison for Power Wind1&Wind2

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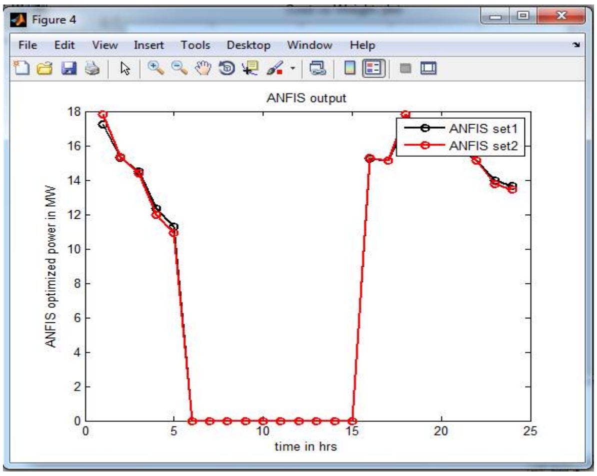

Fig 4.3 ANFIS output

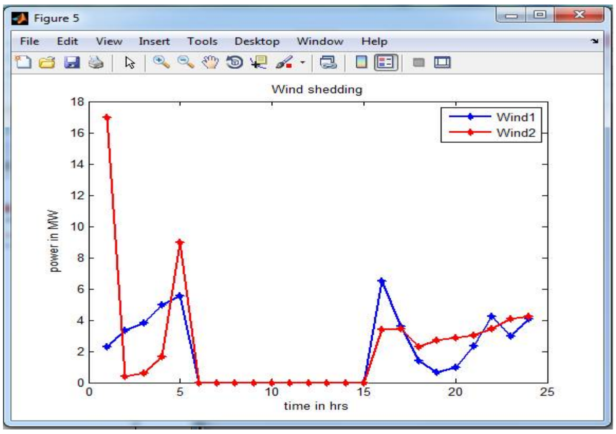

Fig 4.4Wind shed

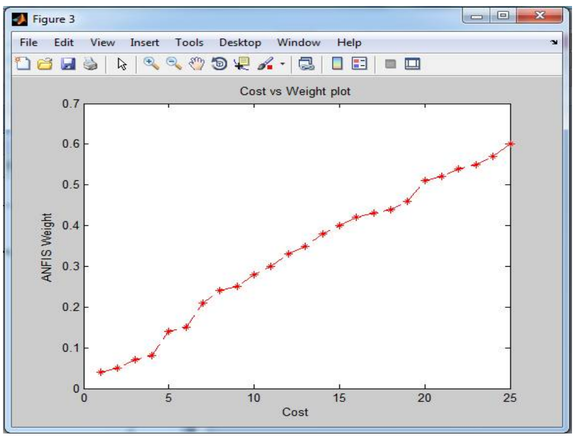

Fig 4.5 cost vs weight plot

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V. CONCLUSION

The two-stage energy and reserve co-optimization model based on interval programming can provide a solution which is robust under a fixed uncertainty set. When considering a larger interval uncertainty set, the system operating risk is low, but the total scheduling cost is high. When considering a smaller interval uncertainty set, the contrary conclusion is obtained. The proposed ANFIS -based energy and reserve co-optimization model considers the softness of the uncertainty set of renewable resources. By transforming the ANFIS mathematical programming model into a mixed integer linear programming model, the model obtains UC, cleared energy, reserve, and renewable shedding for each time period. The solution demonstrates that the ANFIS model can provide a trade-off solution between the system operating risks and total scheduling cost.

VI. FUTURE WORK

The future work may be extended in the way of implementing with the Energy and Reserve Co-optimization with High Penetration of Renewable Energy along with the fruit fly optimization techniques. This behavior is useful to find out which features to be given for the training process with maximum accuracy.

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