FUZZY DECISION MODEL FOR A SMART GRID

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MASTER OF SCIENCE

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ABSTRACT

Electricity is vital for U.S. economy. Over the years, the demand and the usage of electricity have skyrocketed, but the electric transmission and distribution processes have been manual. The current work formulates an automated decision-making model for electric-grid resource allocation. Resource allocation is primarily in the form of assigning the best power source to a sink. The model is built in Fuzzy Logic. The input parameters for the model are the power capacity, the price and the distance. A rule base has been created by domain knowledge and analyzing an operator decision making activity. The Mamdani Min-Max approach of is used for defuzzification. A separate model based on Rough Set analysis has also been constructed to compare the results with Fuzzy model. The results obtained from both models show agreement in decision output and reveal the potential application areas of the Fuzzy model.

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CHAPTER 1. INTRODUCTION

The American electric grid is an engineering wonder due its size and complexity. It is one of the largest electric grids in the world and plays an important role in the U.S. economy. Despite its massive size and critical importance, it has been subjected to intermittent power outages and unusual blackouts. For each interruption, the economic loss encountered is in the order of billions [1]. Many processes and operations involved in the power transmission and distribution process are manually controlled. Currently, the grid operators act as the referees, monitoring activities of the parties and allocating the required power. By its nature, power demand fluctuates highly, and often, there are situations where power demand becomes far more than the system can actually deliver. The system operators have to take special measures to allocate power in those situations. These special measures, in most cases, do not produce the best outcome because decisions need to be made within a very short time. Sometimes, handling a sudden increase in demand becomes unmanageable, and improper handling of the demand results in system failure. The system may also fail when a major power line fails or a big power plant trips offline unexpectedly. The grid operator looks for the problem and tries to rectify it. This process can be time consuming depending upon the nature of failure. The August 14, 2003, blackout in the northeastern United States and parts of Canada indicates how difficult it can be to diagnose a problem before it cascades out of control [2].

The Smart Grid is an answer to the growing complexity of electric-grid operations. The Smart Grid is governed by sophisticated software systems that make the grid more efficient in resource allocation, enable automated decision-making, increase reliability, incorporate renewable energy sources, and produce dynamic pricing between the parties involved. The Smart Grid concept has extended its operation domain from the industrial area to home-electric consumers. The Smart Grid promotes the power delivery to power-consuming utilities and consumers by addressing real-time issues. The attributes of the

Smart Grids can be viewed as follows:

- Increased reliability, reduced peak hour energy demand and overall energy consumption.
- Increased energy usage from renewable energy sources such as wind, solar, tidal, geothermal etc.
- Increased usage of smart equipment, smart meters, and automated control devices, as well as the incorporation of dynamic pricing along with real-time energy usage.
- Enabled a self-healing characteristic of the grid. If one part of the grid fails, the grid will rectify the problem with its logic, intelligence, and historical data.

Because a Smart Grid would automate the electricity transmission, the automated decision-making process would play a major role in its proper functionality. Primarily, the decision-making takes place in the form of resource allocation between the demand and the supply sides. Often, a decision has to be made with a very limited amount of information in hand and within a very short time. Rule-based reasoning, case-based reasoning and model-based reasoning can be considered for the decision making mechanism in a Smart Grid. A short description of each models is given below.

Case-based reasoning is capable of interpreting historical knowledge directly. For a Smart Grid, this decision process is excellent because there is a definite probability that the same failures can happen more than once. Case-based reasoning also allows shortcuts in reasoning. If an appropriate case is found, problems can be solved in much less time than it would take to generate a solution from rules or models. However, case-based reasoning falls short of being an appropriate choice for a Smart Grid because it is not possible to make every single failure case before the failure actually happens. Case-based reasoning scenarios may lack deeper knowledge of the domain. This lack of knowledge handicaps the explanation facilities. In many situations, the reasoning process allows the possibility that cases are not properly created which may then lead to poor-quality advice.

Model-based reasoning uses the functional knowledge of the domain in problem solving. The use of functional knowledge increases the models capability to handle a variety of problems, including those that may not have been anticipated by the systems designers. Model-based reasoning is also very robust in decision-making. This feature is an added advantage for the Smart Grid resource-allocation problem because time is a critical performance parameter with resource allocation. Models often help human beings to have a detailed understanding of the problem domain. However, creating a model is a complex and error-prone process. A great deal of time may be required for a model to become mature in decision-making. A Smart Grid would not be able to sustain any poor or immature decision made by the model.

The rule-based approach can be applied in very direct fashion, and it captures the experiential knowledge of the human expert. The current way of handling power failures can be directly incorporated into the rule-based reasoning, making it an excellent choice for the Smart Grid. The rules can be formed in a modular fashion, which makes its construction and maintenance easier. Decision parameters may change in the course of time; rule-based models are perfectly capable of handling these changes. Fuzzy Logic is a decision making model, which is widely popular because of its capability in making reliable decision with minimal amount of information at hand. Fuzzy Logic is a form of multi-valued logic that deals with reasoning which is approximate rather than exact. It has reasoning in the form of if-then rules in it. In contrast with the binary values of true and false, Fuzzy Logic variables may have a truth property that can be between 0 and 1. In Fuzzy Logic, the concept of partial truth has been incorporated, where the truth value can vary from completely true to completely false. With Fuzzy Logic, the decision-making would be possible with the rules developed when incorporating the experience- driven knowledge of the power operators. Because, the decision-making would be automatic, it will be fast, accurate, and precise.

The concept of a Rough set was first discovered by Zdzislaw I. Pawlak [3]. It is an approximation of the conventional sets as defined in set theory, which is incorporated with the lower, and the upper approximation of the original set. Rough Set have been used in different phases of the knowledge-discovery process, such as attribute selection, attribute extraction, data reduction, decision-rule generation, and pattern extraction (templates and association rules) [3]. Furthermore, recent extensions of Rough Set theory have brought new methods for decomposing large data sets, data mining in distributed and multi-agent based environments, and granular computing [[4, 5]]. Rough Set can also be good choice in rule generation. Rough Sets were designed for the classification of imprecise, uncertain, or incomplete information. This makes it a good fit for a Smart Grid decision making.

1.1. Problem Statement

The current work automates the operator's decision making. Routing decisions are made by this software. The solution incorporates the self-healing characteristic of the Smart Grid. The decision comes in the form of picking the best power source for a particular demand area, so the model is capable of making the routing decisions about which source to connect with which sink or demand area.These decisions are made both by Fuzzy Logic and the Rough Set model. For developing both the models, the initial assumption is to have power sources with an adequate supply. Hence, the supply side always needs a higher amount of power than the demand side. Another assumption is that there should always exist at least one electric transmission route between the region of interest (sink) and the power supply sources (source). The model picks the best power source to connect to a particular sink based on predefined parameters. From Figure 1.1, we can see the demand and the supply side separated by a divider. The demand side consists of localities, such as neighborhoods, municipality, industry etc., while the supply side consists of available power sources or power-generation plans.

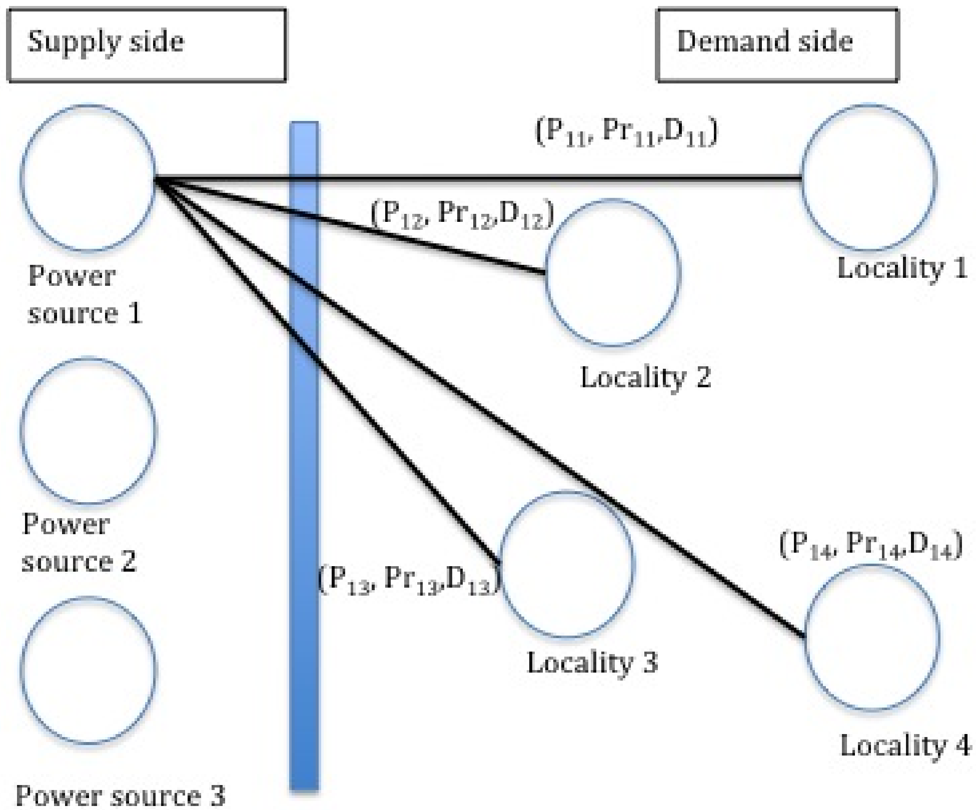

Figure 1.1. Schematic diagram of source and sink.

Now, each power source has a certain capacity in the order of kilowatts, megawatt or gigawatts. If, for a particular scenario, when locality 1 has gone out of power, then we have three options from which to choose to allocate power to that locality. The current model considers all the power sources available and, based on three predefined parameters, finds the best source for electrifying that locality. The predefined parameters are power capacity, price and distance. The process can be further explained with the help of Figure 1.1. We can see that all the localities are specified with attributes. Power source 1 is be evaluated against locality 1, locality 2 and locality 3. For Power source 1, from [Figure 1.1],we can see the parameter vectors indicated as (P_{11}, Pr_{11}, D_{11}), (P_{12}, Pr_{12}, D_{12}), (P_{13}, Pr_{13}, D_{13}), and (P_{14}, Pr_{14}, D_{14}), where P stands for power, Pr stands for price and D stands for distance. The subscript stands for each source and sink combination. So the first 1 stands for power source 1, and the second 1 stands for locality (sink) 1. The combination of each locality and sink is valued in terms of low priority, medium priority, and high priority. For source 1-locality 1, the result can be high priority and for source 1-locality 2, the result can be medium priority. High priority would indicate the best fit, followed by medium, and low priority. For this case, source 1 would be best used with locality 1.

1.2. Objective of the Current Work

The current work investigates the factors associated with creating an automated decision-making platform in a Smart Grid. How a decision model such as the Fuzzy Logic can be applied ? What kind of issues will arise? Further, when the decision-making has been applied, in what kind of situations it might best suited. The work also explores the benefits and drawbacks of a Fuzzy model when compared to other mathematically based decision models. The results from Fuzzy model will be checked with the Rough Set model to ensure the models stability and reliability.To summarize, the objectives of current work are as follows:

1. To develop two alternative decision making models that are capable of making the routing decisions fast and with limited information at hand.

2. To validate and compare the decision output for both the models to see if the results obtained from both the models are consistent with each other.

3. To address the feasibility and reliability issues of the model when applied to the Smart Grid.

The objectives were fulfilled with the development Fuzzy Logic and Rough Set based decision-making models. Rules for the Fuzzy and the Rough Set models were constructed after a detailed analysis of the problem domain and observing operators' decision-making. The results of the both models were compared to understand the potential situations that may arise in automating the resource-allocation process.

CHAPTER 2. BACKGROUND AND LITERATURE REVIEW

2.1. Smart Grid

A Smart Grid is the technology that brings the electric network to the digital age. By enabling the electric grid to be aware of situations that can affect the supply or demand for power, the grid can respond to changes and, at the same time, enable these changes to be an input in determining pricing. Thus, situations, such as transformer failures, or conditions that affect demand, such as heat waves, can be addressed. Perhaps, the most influential factor in driving the adoption of these technologies is the potentially significant savings estimate that the potential benefit over approximately the next two decades will be close to $75 billion [6].

Wissner et al.[7] identified main issues that have triggered the necessity for an efficient grid system. They found, first, the liberalisation of power markets, connected with the unbundling the formerly integrated structures and emerging competition; second, the strong growth of decentralised energy generation, particularly in the field of renewable energies; and, thirdly the need for efficient energy use to reduce greenhouse-gas emissions. In the form of ”ambient intelligence,” a Smart Grid can have automation in virtually all aspects of power generation and distribution. On the generation side, distributed, renewable, small-scale power plants can be connected via information technology. Balancing the power flow can be achieved through broadband communication, and intelligent software would enables the automatic steering of resources. This automation would enhance power-transmission capabilities, and for the distribution side, the demand and supply adjustment would be software controlled. Two-way communication via smart meters would ensure a reduction in energy waste, and the entire system would result in a smart house that can dynamically balance its power consumption.

Ja rventausta et al. [8] studied the performance of a grid with automated meter reading (AMR) systems in a network. A remotely readable energy meter is being developed to be a piece of intelligent equipment (i.e., an interactive customer gateway). The interactive customer gateway will be based on the use of advanced AMR technology and two-way communication between the databases and the applications of the distribution system operator (DSO), transmission system operator (TSO), service providers, and electricity energy-market players (e.g., aggregators).

Clastres [9] highlighted the policy issues regarding the Smart Grid. In his investigation, he found that managing consumption, incorporating renewable sources, and having efficient storage devices in the grid increased the Smart Grid performance. However, it was noted that along with economic implementation challenges, there exist some other policy-level decisions that are not resolved. Dynamic pricing scheme, surplus skimming procedure, regulations, and incentives for new network incorporation are important among them.

There have been numerous attempts to create simulation systems for a Smart Grid environment[10],[11], [12]. In [10], the authors created an accurate hardware simulation of a simple microgrid using MATLAB and Simulink to implement low-level electric circuits' functionality. The authors attempted to prove that the basic concept of an intelligent distributed autonomous system, consisting of a micro-grid combined with intelligent agents, would work properly. Their agent implementation was very simple. It mostly involved simple voltage monitoring to activate a circuit breaker and secure critical loads, without any complex decision making. The agent interaction and collaboration were not thoroughly tested, evaluated, or analyzed in their simple simulation; their focus was more on proving a micro-grid that can be managed as part of the global grid and still able to work autonomously in "island" mode. In [11], an adaptive, self-healing framework for power grids based on intelligent-agent technologies is proposed, but little information is presented about any actual working simulation. In [12], an agent based simulation of a dynamic smart city is implemented; the simulation is promising because it has a degree of flexibility.

2.2. Automated Decision Making

Dua et al. [13] incorporated Integer Linear Programming as a decision model for the placement of Phasor Measurement Units (PMU) over an electric grid. PMUs provide a time-synchronized power measurement for a power system. The authors were trying to identify the minimal number of PMUs to be placed to capture the grid's power information. In their Integer Linear Programming model, the authors incorporated zero injection constraints to achieve the minimal number of PMUs. The authors also found that optimal PMU placement had multiple solutions. However, the solution with the maximum System Observability Redundancy Index (SORI) produced the best result in their case.

Hennebry et al. [14] constructed an Integer Linear Programming based decision-making model to search, classify, attack, and perform battle damage assessment of enemy targets for Unmanned Air Vehicles (UAVs). For Hennebry et al.'s particular situation, forming sub teams to attack a single, important target seemed more feasible. The Integer Linear Programming model was successfully able to handle those situations. The performance of the heuristic model was compared with the optimal solution. The %error varied from 0.13% to 0.63% with different sub-team formations. The error of the heuristic was consistently small and was arguably close to the optimum for practical use, specially noting that there are likely to be data inaccuracies in the data in a real situation. The authors concluded that with the Integer Linear Programming model, good solutions for the sub-team formation problem can be quickly and accurately generated.

Ranganathan and Nygard [15] formed a resource-allocation model for a smartgrid in a Binary Integer Programming concept. The model can assign Distributed Energy Resources (DERs) to available Regional Utility Areas or units (RUAs) that are experiencing power shortages. This approach is called capacity-based Iterative Binary Integer Linear Programming (C-IBILP). All simulation results are computed using the optimization tool box in MATLAB. The results showed that the optimal value was reached after 163 iterations with 54 nodes participating in 1.22 seconds when using the capacity based Iterative Binary Integer Linear Programming (C-IBILP) based branch and bound method which maximizes the satisfaction of the DER preferences weighted by the model capacities. For another case, when the preferences of DERs were changed, then the optimal solution was reached with 13 iterations and 0.047 seconds with default node and branch strategies.

Barnes et al. [16] constructed a decision-making platform based on the Group Theoretic Tabu Search (GTTS) for the Air Fleet Refueling Problem (AFRP). The article described how the AFRP for the Air Mobility Command (AMC) at Scott Air Force Base, is efficiently solved using Group Theoretic Tabu Search (GTTS). GTTS uses the symmetric group on n letters (Sn) and applies it to this problem using the Java language. Using the Tabu Search approach, Barnes et al. were able to find some critical, mission-specific parameters, i.e., the number of tankers needed, the time of the operation, the distance needed to travel, the amount of fuel burned in refueling an aircraft, etc. Sun et al. [17] performed the Tabu Search heuristic procedure for a Fixed-charge transportation problem with network-based implementation of the simplex method in the form of a local search method. Their model was computationally successful when compared to other models. Belfares et al. [18] studied a multi-objectives resource (time, resource, etc.) allocation problem. Their objective was to find adequate resource allocation for the schedule of some given courses of action. To optimize this problem, the article investigated a progressive resource-allocation methodology based on Tabu Search and the multi-objectives concepts. The model was guided by the principle of maximizing the usage of any resource before considering a replacement resource. The performance of the approach was compared to two aggregation approaches: weighted-sum and the lexicographic techniques. The result showed that the developed approach provides better solutions and allows more exibility for the decision-maker. Vadde et al. [19] presented a model for Product Recovery Facilities (PRF) which passively accepts and acquires discarded products from the customers, when required. The model considered that PRFs process multiple types of discarded products. A multi-criteria based Genetic Algorithm was employed to solve the optimization problem. The scalar objective function, obtained through the weighted sum approach, was maximized. The work assumed that the decision maker would assess the contribution of each criterion to the overall objective function. The model determined the prices for reusable and recyclable components as well as the acquisition price of discarded products. The model involved conflicting objectives to maximize revenue from a sale and to minimize product-recovery costs, such as disposal cost, disassembly cost, preparation cost, holding cost, acquisition cost, and sorting cost.

Fanti et al. [20] created a model for job scheduling in flexible production systems. The job scheduling is done using the Fuzzy Set theory and the Genetic Algorithms. In the production systems: the scheduling objectives are multi-facetted and conflicting with each other; the scheduling approaches are heuristic; and discrete event simulation based performance measures have been used. In this work, Fuzzy Logic enables decision-making and a means to define performance measures by combining different production objectives. The evolutionary algorithms are able to solve optimization problems lacking any information relating decision variables. The numerical experiments confirm the effectiveness of the approach. Arroyo and Armentano [21] proposed a genetic local search algorithm with features such as preservation of dispersion in the population, elitism, and the use of a parallel multi-objective local search to intensify the search in distinct regions. The developed genetic algorithm based concept is applied and compared with Branchand-Bound algorithms proposed in the literature. For instances involving up to 80 jobs and 20 machines, the performance of the algorithm is compared with two multi-objective, genetic, local-search algorithms proposed in the literature. Computational results show that the proposed algorithm yields stable results.

Zadeh [22, 23, 24]performed initial work in formulating, Fuzzy Logic. In his work [22], he introduced Fuzzy Sets, an extension of the classical notion of a set. In Fuzzy Sets, gradual assessment of membership of elements is possible in the form of the membership function. The article also explained how the notions of inclusion, union, intersection, component, relation, convexity etc. apply to Fuzzy Sets. In his later work [23], Zadeh extended the idea of Fuzzy Sets to implement the concept of a Fuzzy algorithm. In the article, the process of converting a relational representation into algebraic form was discussed. Zadeh [24] explained how Fuzzy algorithms can be applied in complex, ill-defined problems. These problem domains were not limited to economics, management science, psychology, linguistics, taxonomy, artificial intelligence, information retrieval,medicine, and biology.

Greco et al. [25] performed multi-criteria decision making with Rough Set analysis. They created a decision rule system for multi-criteria decision analysis (MCDA) problems, sorting problems, and choice or ranking problems. In Rough Set the main change is the substitution of the indiscernibility relation by a dominance relation, which permits the approximation of ordered sets in multi-criteria sorting. However, with substitution of the data table with a pairwise comparison table, where each row corresponds to a pair of objects described by binary relations on particular criteria, the authors have been able to make decision rules from Rough Set analysis. Kryszkiewicz et al.[26] developed an approach to reason for incomplete information systems. They proposed the reduction of knowledge that not only eliminated that information, but also was not essential from the point of view of the classification or the decision making. They made only one assumption about the unknown values: ”the real value of a missing attribute from the attribute domain." They have found decision rules directly from an incomplete decision table; the decision rules were non deterministic and had a minimal number of conditions. Jensen and Shen [27] created a hybrid decision model on the Fuzzy and Rough Set theories for web data redundancy; only information-rich data were processed. The model was applied to the problem of web categorization and the model considerably reduced dimensionality with minimal loss of information. They found that both the hybrid model and solitary Rough Set based model can be used in decision making. Dimitras et al. [28] performed a business failure prediction analysis with Rough Set. In the article they showed a set of rules that can determine healthy and failing firms. They created the rules with a sample set of 80 greek financial institutions and then used the model to predict health of each institution. Skowron and Suraj [29] created a parallel algorithm for a real-time decision-making engine based on Rough Set. They considered the decision tables with the values of conditional attributes measured by sensors. With the help of petri nets, they were able to identify objects in the decision tables to an extent that made possible appropriate decisions possible.

CHAPTER 3. FUZZY LOGIC SMART GRID MODEL

In this chapter, the consturction of a Fuzzy Logic decision model is discussed. First, the idea of crisp and Fuzzy Sets is briefly described. Afterwards, the essential components needed to construct a Fuzzy Decision Model are introduced, followed by the model creation for the Smart Grid.

3.1. The Fuzzy Model

A Mamdani type Fuzzy Controller has four components [Figure 3.1]:

1. Fuzzifier

2. Knowledge Base

3. Inference Engine

4. Defuzzifier

3.1.1. Fuzzifier

The fuzzifier performs measurements of the input variables (input signals). All the monitored input variables are scaled, and the crisp input quantities that have numerical values are transformed into Fuzzy quantities (which are also referred to as linguistic variables in the literature). This transformation is performed using membership functions. The classic set, as we know from set theory is a crisp set which has a concrete definition of its boundary. For example, if set A can consist of real numbers greater than 10, then it can be expressed as,

$$A = \{x|x \geq 10\}$$

Here, a clear and precise boundary is defined as no number greater than 10 can be a member of the set. The decision is precise in its term because we can tell that a particular number is either a member or not a member of the set. In real life, we may not be able

Figure 3.1. Fuzzy model creation stages.

to define everything so precisely as of ”yes” or ”no.” If we consider in the context of human concepts and thoughts, we will find many situations where human thoughts tend to be abstract and imprecise. There may not be a clear boundary for decision-making. As an example, we can consider a sensor for controlling room temperature. If we want to configure the sensor, we have to set it to a precise value, such as 70 degrees F, to be the criterion of the high temperature. If the room temperature reaches 69.5 degrees, the sensor will interpret that it is not hot, i.e., cold. If we consider in the context of human beings, then there will not be any difference between the 69.5-degree and 70-degree temperatures. To capture this degree of abstractness, the Fuzzy Set, which does not have a crisp boundary, has been formed. In Fuzzy Sets the decision is made with the membership functions. A Fuzzy set A in x is defined as a set of ordered pairs as follows:

$$A = \{(x, \mu A(x)) | x \in X\}$$

where μA is called the membership function for the Fuzzy set A. The value of A varies from 0 to 1. X is referred to as the universe of disclosure, which is basically the collection object. The universe may consist of continuous or discrete (ordered or unordered) objects. If the universe of discourse X is a continuous space, they may be segmented into several Fuzzy Sets and referenced according to our daily linguistic terms, such as ”large,” ”medium, ” or ”low.” These values are called linguistic values or linguistic labels.

The *membership function* of a Fuzzy Set is used to determine the degree of truth for a user input value against the Fuzzy Sets member variables. Membership functions can come in triangular, trapezoidal, gaussian, bell shaped and sigmoidal form. In a model, more than one of such functions can be used to construct a single membership. In this Smart Grid model, the triangular membership function is used along with the trapezoidal membership function.

3.1.2. Knowledge Base

The Fuzzy reasoning process involves data and linguistic control rules or if then rules. This is called a knowledge base. After getting a particular input from the user, the Fuzzy Controller interacts with the data and the rules simultaneously to determine the output. The data provide the information for the linguistic control rules, and the rule base (expert rules) specifies the control goals. The rule base contains a set of if-then rules. The rules are generated in many ways, depending upon the problem domain. Rules can be formed in a combination of user experience, expert's domain knowledge, modeling the action of the operator, process observation, and gradual learning, etc.

3.1.3. Fuzzy Inference

The Inference Engine (reasoning mechanism) is the kernel of the Fuzzy Controller. It works with the linguistic variable to obtain the result. The linguistic variables come in the form of words used in day-to-day language expression. The inputs to the Fuzzy system such as ”Power Capacity,” ”Displacement,” ”Velocity,” etc. may be considered as linguistic variables. To quantify the values the linguistic values can be expressed in the form of ”Low,” ”Moderate,” ”High,” etc. The values can be further divided in to ”Very low,” ”Moderately high,” etc. Once the linguistic variables and their values are defined, the rules map the Fuzzy inputs to Fuzzy outputs through the Inference Engine. The Inference Engine triggers the if then rules based on user input. A Fuzzy if-then rule (also known as Fuzzy rule) assumes the following form: If x is A, then y is B, where A and B are linguistic values defined by Fuzzy Sets on X and Y, respectively. ”x is A” is the antecedent, or premise, while ”y is B” is the consequent, or conclusion. In this way, all input variables are converted into linguistic variables, and Inference Engine evaluates the value within the set of if-then rules. Then, a result is obtained with the linguistic variables in Fuzzyfied form.

3.1.4. Defuzzification

The result obtained from the Inference Engine needs to be converted back into a crisp value. This process is known as Defuzzification. In Defuzzification may consist of scale mapping factors similar to the ones used in the Inference Engine rule-generation process. However, this time, the output comes in the real-world decision context. The Deffuzzifier may also use membership functions to generate real-world output. There are several Defuzzification techniques, such as the Center of Area, the Mean-Max method, the First of Maxima method, the Last of Maxima method ect. In the current controller the Mean-Max method is used for Defuzzification.

3.2. Fuzzy Controller for the Smart Grid

The Smart Grid Fuzzy Controller is capable of making automated decisions for resource allocation. It takes some predefined inputs, and then based on the given parameters, it picks the best source to connect with a sink. First, the Fuzzy variables are identified. In the Smart Grid model, the power capacity of source, the price to generate unit power and distance between the source-sink are considered as inputs for the Fuzzy model. These three parameters are named as power, price and distance. After that, the membership functions are constructed. The membership functions have the trapezoidal and triangular functions. The input parameters are described below.

Power: The power capacity is the first input parameter. The power of the source has been divided into three categories: Low, Medium and High (Figure 3.2). The low power value starts at 0 and goes all the way up to 500 units; beginning at 300 units, it starts to overlap with medium. Similarly, the medium starts at 300 and overlaps with high at 500 units. After 700 units, all the values are considered as high. The unit of power is mega-watts (MW) but the unit can be assigned as something else, too. All the input values of power are fuzzified using the membership function in the range of 0-1. We want to maximize the amount of power utilization, so for rule generation, a higher power will get more priority.

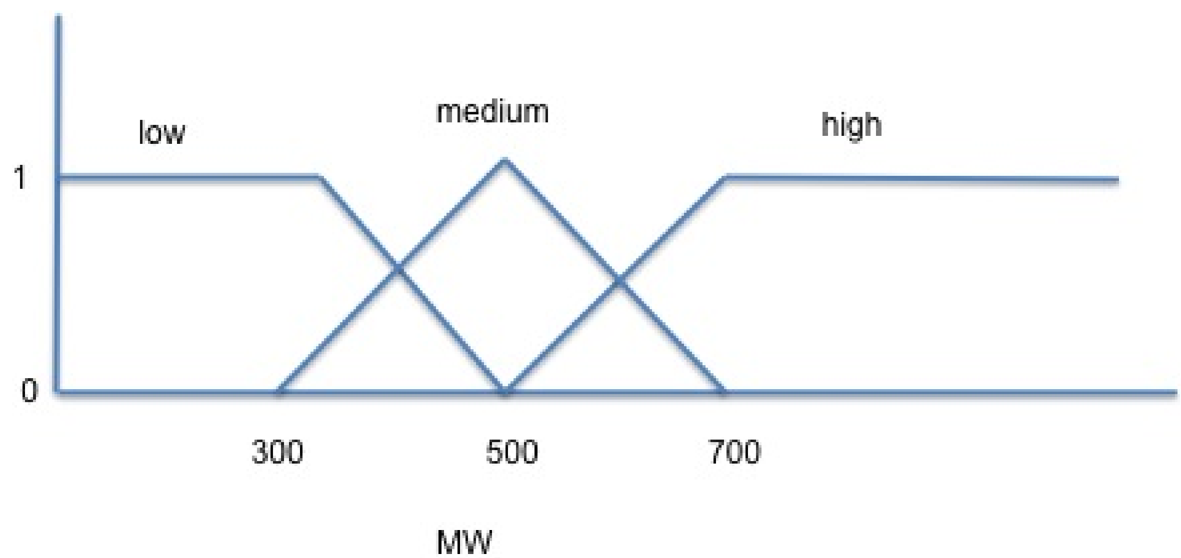

Figure 3.2. Power membership function.

Price: The price of power generation is the second variable and is also divided into three categories: Low, Medium and High (Figure 3.3) . The low value starts at 0 and goes all the way to 6 units; beginning at 3 units, it starts to overlap with medium. Similarly, the medium starts at 3 and overlaps with high at 6 units. After 9 units, all values are considered high. The unit is dollars/day. All the input values of power are fuzzified using this function in the range of 0-1. We want to give priority to the source which is offering power at a lower price, so a lower price will get more priority.

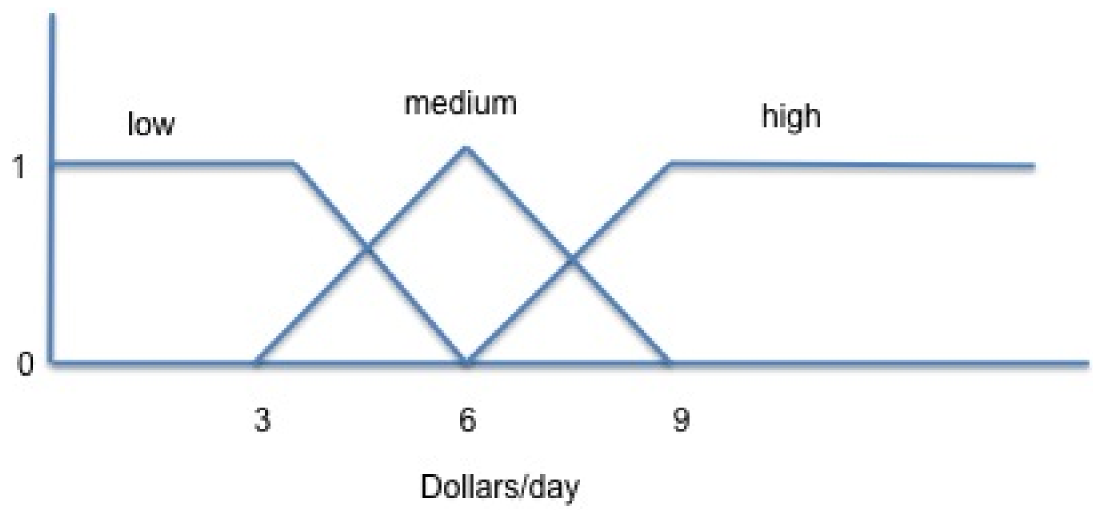

Figure 3.3. Price membership function.

Distance: The last Fuzzy variable is the distance between source and sink. It is also divided into three categories: low, medium and high (Figure 3.4). The low value starts at 0 and goes to 5 units; beginning at 3 units, it starts to overlap with medium. Similarly, the medium starts at 3 and overlaps with high at 5 units. After 10 units, all the values are considered high. The unit is miles. All the input values of power are fuzzified using this function in the range of 0-1. We want to give priority to the source which is closer to the demand area, so a lower distance will get more priority.

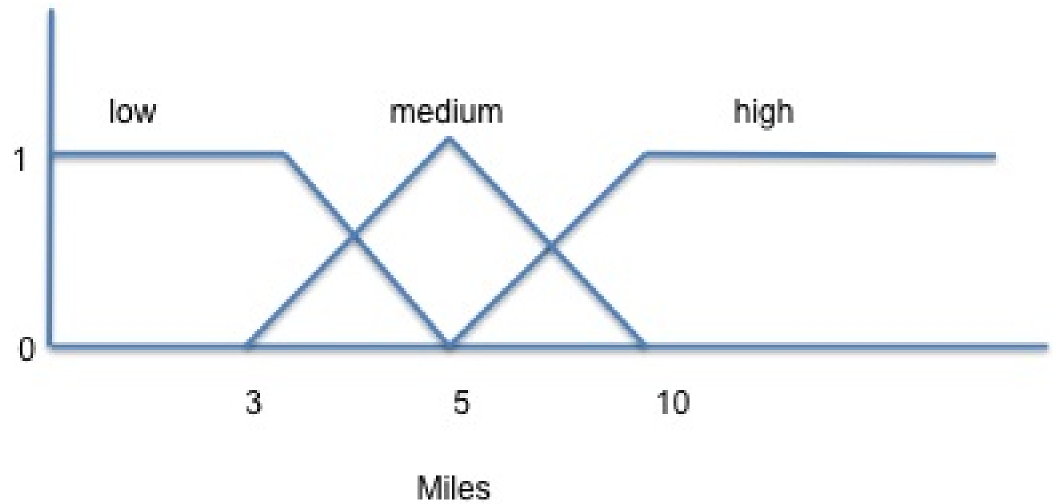

Figure 3.4. Distance membership function.

Inference Engine: Because there are three Fuzzy variables and because, for each variable, there are three different outcomes, the total number of rules is 27. Table 3.1 lists all the rules. These rules are if-then rules.The outcome of the rules is considered in terms of priority level. This linguistic outcome clearly captured the notion of the input. The output with a high priority would generally be preferred over low or medium priority. A detailed description of the output is presented in the Procedure Description section. To understand the decision making process more thoroughly, let us consider a situation where based on user input, rule 1 is triggered; then, for that case, the model would interpret as follows: if power capacity is low, price is low, and distance is low, then the result is a low priority in assigning that power source with the sink.

Defuzzification: The defuzzification process produces a real-life output for the input set provided. In this model, the Min-Max approach is used for interpreting the Fuzzy results. In Min-Max analysis, the minimum values of the Fuzzy variable set are considered in the first stage. Then, for these values, the rule output is associated with the minimum values. The maximum value with the rule output is then considered as the model output.

Table 3.1. Fuzzy rule base.

Rule no.	Power capacity	Price	Distance	Decision	Order
1	low	low	low	low priority	1
2	low	low	med	low priority	4
3	low	low	high	low priority	7
4	low	med	low	low priority	10
5	low	med	med	low priority	13
6	low	low	high	low priority	16
7	low	high	low	low priority	19
8	low	high	med	low priority	22
9	low	high	high	low priority	25
10	med	low	low	medium priority	2
11	med	low	med	medium priority	5
12	med	low	high	medium priority	8
13	med	med	low	medium priority	11
14	med	med	med	low priority	14
15	med	med	high	low priority	17
16	med	high	low	low priority	20
17	med	high	med	low priority	23
18	med	high	high	low priority	26
19	high	low	low	high priority	3
20	high	low	medium	high priority	6
21	high	low	high	medium priority	9
22	high	med	low	high priority	12
23	high	med	med	high priority	15
24	high	med	high	medium priority	18
25	high	high	low	medium priority	21
26	high	high	med	medium priority	24
27	high	high	high	low priority	27

3.3. Procedure Description

The above narrative gives a qualitative explanation of the Fuzzy model construction and decision-output process. However, a more detailed description is presented in this section with the help of a real-life scenario that may be encountered. As an input let us consider X=[400,8.5,3], where power = 400 MW price = 8.5 dollars, and distance= 3 miles. From the membership function of power, price, and distance, we obtain the following values as shown in Table 3.2.

Table 3.2. Fuzzy input values used for procedure description.

Variable	Low	Medium	High
Power	0.5	0.5	0
Price	0	0.2	0.8
Distance	1	0	0

Once the values have been gathered from the membership functions, the Inference Engine triggers the rules. For each of the Fuzzy variable set, the minimum value is chosen. The rules, along with their values are shown below:

If power capacity is low, price is high, and distance is low, then there is low priority (take the lowest) :

$$0.5 \wedge 0.8 \wedge 1 \Rightarrow 0.5$$

If power capacity is low, price medium, and distance low, then there is low priority:

$$0.5 \wedge 0.2 \wedge 1 \Rightarrow 0.2$$

If power capacity is medium, price high, and distance low, then there is low priority:

$$0.5 \wedge 0.8 \wedge 1 \Rightarrow 0.5$$

If power capacity is medium, price medium, and distance low, then there is medium priority:

$$0.5 \wedge 0.2 \wedge 1 \Rightarrow 0.2$$

Now, for each Fuzzy variable set from the rule base the linguistic rule output would be associated with the minimum values. Therefore, we have the following:

$$\text{Case 1 : Low priority} \Rightarrow 0.5$$

$$\text{Case 2 : Low priority} \Rightarrow 0.2$$

$$\text{Case 3 : Low priority} \Rightarrow 0.5$$

$$\text{Case 4 : Medium priority} \Rightarrow 0.2$$

Hence, we have the low-priority output and one medium-priority output. In the Min-Max analysis, we take the highest value along with the priority levels. The final value for low priority would be 0.5. Therefore, for this input case, the Fuzzy model would produce low priority.

3.4. Rough Set

An alternative decision making model is created based on the Rough Set approximation. The Rough Set based decision model is more concrete in terms of the boundaries defined for a particular set, hence it is less granular in nature. However, the decision-making mechanism is less computationally intensive in the Rough Set. The current model is build for the purpose of comparing the Fuzzy-decision output. The results from both the models gave a detailed insight about outputs of each model. Because the Rough Set model is primarily built to compare Fuzzy results, the basic construction of the Rough Set model is very similar to the Fuzzy model. The same rule base and

Inference Engine have been used to construct the Rough Set model. Similar to the Fuzzy model, the input parameters are kept the same. Power capacity, price, and distance are the input parameters used for making a decision.

Fuzzy Logic does not provide any specific boundary. For example, if we see the power membership function in Figure 3.5, we notice that the segment boundaries of low, medium and high does not necessarily have any concrete value for their ranges.

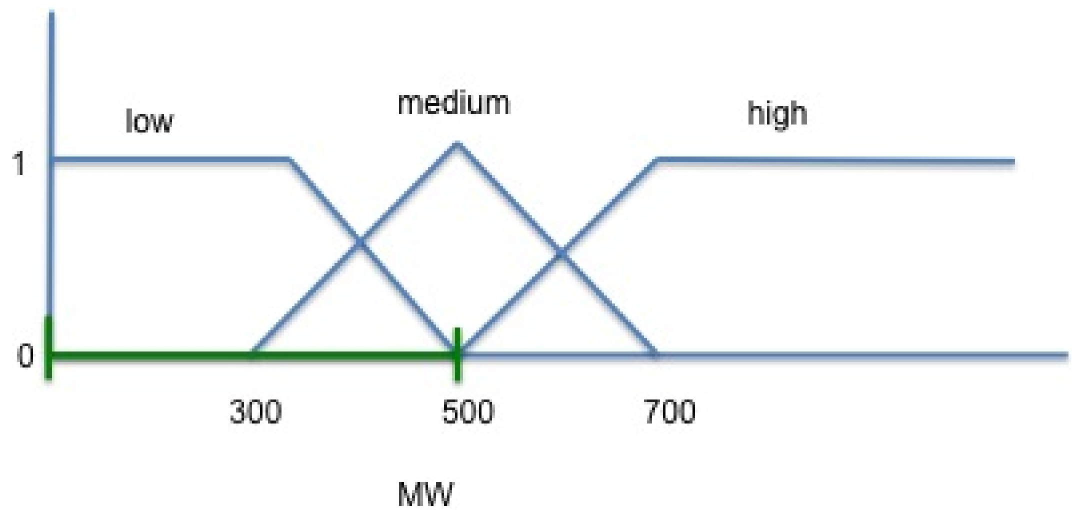

Figure 3.5. Fuzzy membership function.

For power, the low range starts at 0, eventually ending at 500, and after 300, it starts to overlap with the medium range. That overlap influence is less at the beginning, i.e., at 300, and gradually starts to become higher after 500. However, in Rough Set, the idea of the membership function does not exist, so we need to define a more concrete boundary. The values for each member variables have been changed. For power, price and distance the terminal values that are used to define the boundary for low, medium, and high are presented below in Table 3.3.

Table 3.3. Rough Set input domain.

Input	Low	Medium	High
Power(MW)	50-250	250-650	650 >
Price(Dollar)	1-4	4-8	8>
Price(Miles)	1-3.5	3.5-7	7>

From Table 3.3, we can see the difference in the level of the inputs. Once the values are obtained from the input set, the rules are fired based on the Decision table (Table 3.4) created for the Fuzzy Logic. As the rule base is kept identical, the model will produce similar results as of the Fuzzy model. The Fuzzy model has 27 different rules in the rule base. Because, the Rough Set model will just compare the results with the Fuzzy model, not all 27 rules are mapped. The rule output, that has a low priority, is not considered for the Rough Set rule base. Only the outputs with medium and high priorities are mapped into the Rough Set rule base. The rule output is the same. The rule base with output is shown in the Table 3.4. From Table 3.4, the input parameters, along with the decision output for the high and medium priority levels can be seen. The table also incorporates two additional columns: rank and segments. The decision outputs are further segmented in the high and medium range with rank 1 having more priority than rank 2. Similarly, the medium priority levels are also segmented into medium levels. All the outputs are ranked in terms of priority. A rank of 1 is the best solution followed by ranks 2 and 3; eventually rank 12 would have the lowest priority.

Table 3.4. Rough Set test case values.

Power	Price	Distance	Decision	Segment	Rank
high	low	low	high priority	high	1
high	low	medium	high priority	high	3
high	med	low	high priority	high	4
high	med	med	high priority	high	2
medium	low	low	medium priority	med	6
medium	low	medium	medium priority	medium	11
medium	low	medium	medium priority	medium	12
medium	medium	low	medium priority	medium	7
high	low	high	medium priority	medium	5
high	medium	high	medium priority	medium	8
high	high	low	medium priority	medium	10
high	high	medium	medium priority	medium	9

The Rough Set model gets user input values of power, price and distance for a particular demand location. Based on the input, divide the values into low, medium, and high boundaries. Then, check the necessary rules to reach decisions. Based on the decisions, the model will take the terminal decision that has the highest rank for the final output.

3.5. The Model

To build the Fuzzy model, four different classes are created. Fuzzy member, rule base, inference and defuzzification. Four classes are used to assign different activities associated with each class into a more coherent and traceable manner. Each class has different methods assigned to carry out the necessary responsibilities. The overall process can be seen in the sequence diagram for the Smart Grid Fuzzy model (Figure 3.6).

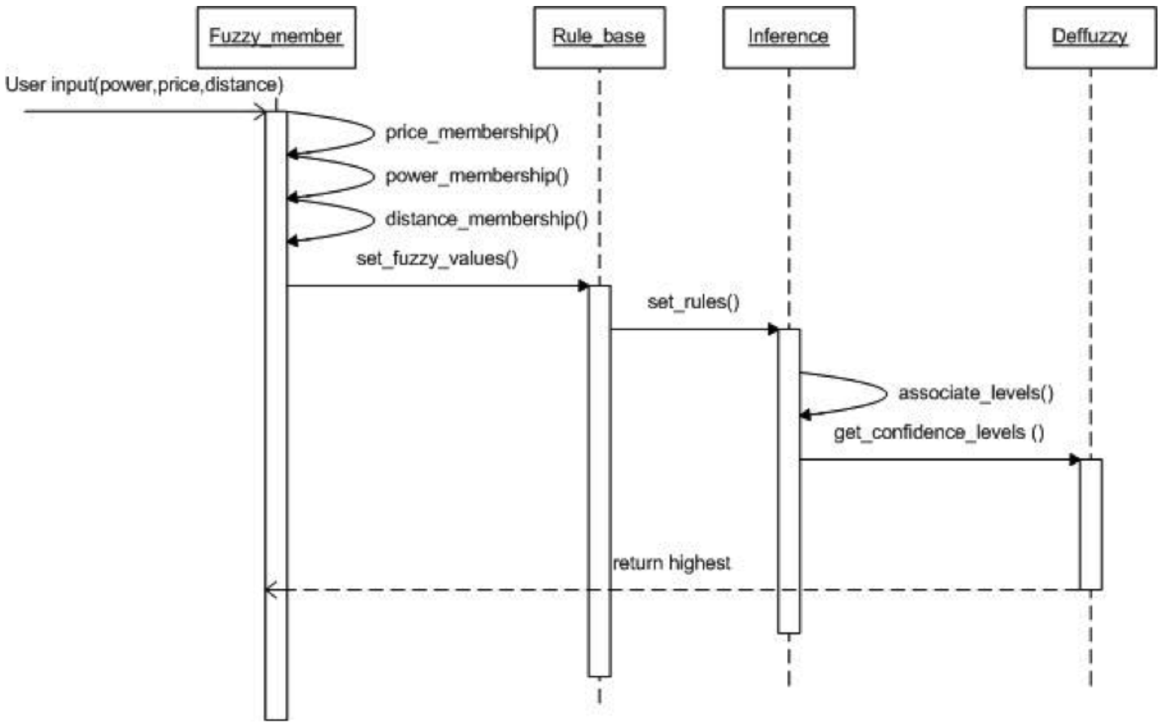

Figure 3.6. Sequence diagram of Smart Grid Fuzzy model.

First, the user input set with power, price and distance are taken by the Fuzzy member class. Then the class assigns each input value with appropriate membership functions. In the membership function, the fuzzification process is carried out, and the output value is passed to the rule base where the values are mapped with each rule. The rule-base output is passed to inference where rule outputs are assigned to each priority level. Finally, in defuzzification, the highest value is returned as the model output. The model is constructed in the C++ programming language under with a gcc compiler.

CHAPTER 4. RESULTS AND DISCUSSION

In this chapter, the results obtained from the test runs of the Fuzzy and the Rough Set models are presented. The testing procedure is also explained along with the findings that have been gathered during the execution and design of test cases. First, in Section 4.1, the Fuzzy model testing issues are addressed. In Section 4.2, the Rough Set model issues are discussed, followed by routing-decision outputs in Section 4.3. Finally the Scalability issues are outlines in Section 4.4.

4.1. Testing the Fuzzy Model

From the rule base, it can be seen that, among the total of 27 rules, 15 falls in into the low-priority region, 8 into the medium-priority region and 4 into the high-priority region. For testing, 10 random input values are taken in such a fashion that would trigger the medium- and the high-priority rules from the Inference Engine. For each input set, the expected output, based on domain knowledge and with Fuzzy model, is listed in Table 4.1. In Table 4.1, the values of each input set are listed in each column corresponding to the input variable's name. For example, for an input set of 600,4,15, the power fell into the medium range; the price fell into the low range; and the distance fell into the high range. From the rule base, this input will trigger rule number 12, which has a rank of 8. If we see the rule base for this input, the expected output is medium priority. The column-model output enlists all the values produced by model for each priority level. It can be seen that, for medium priority, the output has the highest value. Hence, for this input, the model output is also medium priority. Similar explanations can also be established for the remaining values shown in the table. For the input set of 400,1,1, and interesting output is seen. It has identical values of medium and low priority. The reason for this output is that the input value of 400 falls into the interface of the low and medium regions in the power

Table 4.1. Input and Output values used in testing the Fuzzy model.

No.	Power (MW)	Price (Dollars)	Distance (Miles)	Expt. result	Model Output Low	Med	High	Model Result
1	600	4	15	Med priority	0.33	0.667	0	Med priority
2	800	2	2	High priority	0	0	1	High priority
3	800	2	12	High priority	0	1	0	High priority
4	800	2	6	High priority	0	0.2	0.8	High priority
5	850	7	2	Med priority	0	0.667	0.33	Med priority
6	850	2	7	High priority	0.4	0.6	0	High priority
7	900	7	12	Low priority	0.66	0.33	0	Low priority
8	300	2	12	Low priority	0.75	0.25	0	Low priority
9	400	1	1	Low,Med priority	0.5	0.5	0	Low,Med priority
10	700	6	7	Med priority	0.4	0.6	0	Med priority

membership function, whereas the price and distance input values are all low and have a minor influence in the model output. This scenario is discussed further in Boundary Condition Checks section.

The set of these 10 inputs gives us a reasonable understanding about the working pattern of the Fuzzy model. The model output and expected output matched in all instances. Heuristic based models cannot be tested with all possible combinations. The 10 inputs chosen to run the test can be considered reasonable. With these input-output combinations, it can be observed that the model has produced results that are practically expected under those parameters.

4.1.1. Tests with Varying Parameters

In the Fuzzy model, the input parameters of power, price, and distance are mutually dependent on each other in generating the final result. If we carefully observe the rules, we will see that the priority level increases as the power value increases. In practical terms, it will always be beneficial to choose a power source, which will have more power available. Similarly, for the price, and the distance, it will be beneficial if a lower cost and a smaller distance can be found to transfer the power. A lower cost will save money, and a smaller distance will save the amount of heat and other losses encountered during the path. For a particular power source, lower values for price and distance will have more preference than higher values of price and distance. This concept has been put into the Fuzzy model to analyze its output. To test the model, the inputs shown in Table 4.2 were considered.

Table 4.2. Test values for the Fuzzy model with varying parameters.

No.	Power(MW)	Price(Dollars)	Distance(Miles)	Result
1	900	3	3	High priority
2	900	3	4	High priority
3	900	7	12	Low priority

A closer look at the results obtained will clearly explains the concept presented in the last paragraph. For the first input, the power is in high; the price is in low, and the distance is in low. Hence, the result is of high priority. As the distance increases from 3 to 4, no change in the model output is observed. In the third case, the price and the distance values are significantly high enough to change the overall outcome of the result. The price value of 7 fell into the medium-to-high range, where it is more inclined towards the high side.

The distance value is 12, so it will have no influence of the medium boundary and will be completely high.For the third case, the result produced by the model is of low priority. From the rule base, if the power is high,the price is high, and the distance is also high, then the output is low priority.

If there is a situation where the customer is only concerned about the price and does not want to take the distance into consideration, then the current model is able to accommodate that scenario, too. In that case, the distance value needs to be set to zero, and the decision output will gives the result. For this case, the model is only taking two parameters and making its decision based on them.

4.1.2. Tests with One Parameter Changing

Another interesting pattern obtained from the Fuzzy model is the quantitative change in the output priority values. For a particular input set, if the two input parameters are kept unchanged and the third parameter is changed gradually, then the numeric value of result captures this change quantitatively. If the power and the price values are kept constant while the distance value is increased gradually, then a quantitative change in the output is observed until the change is high enough to alter the final result. For testing changing condition of one parameter, the test values are listed in Table 4.3.

Table 4.3. Test values for the Fuzzy model with one parameter changed.

No.	Power(MW)	Price(Dollars)	Distance(Miles)	Result
1	900	3	3	High priority (1)
2	900	3	4	High priority (0.5)
3	900	7	11	Medium priority (1)

From the results shown in Table 4.3, it can be seen that, initially when the power, price, and distance values are 900,3,3, the model output is high priority, and it has been verified with the rule base. However, as the distance value is increased, the quantitative value of high priority starts to decrease, but the change is not high enough to trigger a different rule from the Inference Engine. Finally, for the third output, the change has triggers a different rule output because the priority level changes in the output.

4.1.3. Boundary Condition Checks

Boundary-value analysis is an approach that can be used to test any model. The idea of boundary-value analysis is to check if there has been any unexpected change in the output if the input values were changed close to the boundary. To test any model with boundary-value analysis, a clearly defined boundary is needed. In Fuzzy Logic, the concept of a boundary is fluid, and it does not have any clear boundary. If we check the membership functions of power, price, and distance in Figures 3.2,3.3, and 3.4, we can see that there is always an overlap between the boundaries with the low boundary overlapping with the medium boundary and the medium boundary overlapping with the high boundary. However, after a certain point, all values in each membership function is all low or all high. The concept of the boundary value has been applied here in the Fuzzy model in an abstract fashion. The values are taken from the intersection points of the boundaries. At the intersection point, the model is supposed to produce a similar weight for both the levels. For example, if we consider power value of 400, then it will fall in the intersection point of the low and medium ranges. The value can be plugged into the model to see what output the model is producing. This case is tested in the model with the following inputs listed in the following Table 4.4.

Table 4.4. Test values for the Fuzzy model boundary condition check.

No.	Power(MW)	Price(Dollars)	Distance(Miles)	Result
1	400	8.5	3	Medium priority (0.5)
2	600	5	4	Med(0.5),High (0.5)
3	600	5	8	Low priority (0.6)

The model output shown in Table 4.4 presents an interesting pattern. The input values are on the intersecting region, hence, the both boundary conditions incorporate identical values for each input, we see that both medium and low priorities have a similar output. For the third output, we can see the low-priority value is 0.6, which is very close to 0.5. The identical values for both priority levels create a delay in decision-making. A change in the membership function may be necessary to avoid this situation. Instead of being symmetrical among the boundaries for low, medium, and high, the membership function boundaries can be non symmetric so this situation can be avoided.

4.2. Comparison with Rough Set

The Rough Set model used the same rule base as of the Fuzzy model. However, for Rough Sets, the boundaries are more rigid than with Fuzzy Sets. Rough Sets incorporate clear and distinct boundaries, so different values are used to define the boundaries in Rough Set. To compare the results between Rough Set and Fuzzy Logic, the chosen input values need to fall into the same boundaries. Otherwise, results cannot be compared.
In Figure 4.1, the membership function of the power capacity is shown along with the superimposed boundaries used for the Rough Set. From the figure, the strict boundary for the power in the Rough Set can be seen. For example, when the power goes beyond 250, it will be all medium with no influence of the low range. However, for Fuzzy Logic, there will be an influence from the low range. A similar explanation can also be extended for

the case of price and distance membership functions in Figure 4.2, and 4.3. Because the boundary values are different for the Fuzzy and the Rough Set, to compare the results, input values need to be picked from overlapping portions of the Fuzzy and Rough Set boundaries. The input values, along with the model outputs, are presented in Table 4.5. A total of four input sets are tried in both models to determine the output.

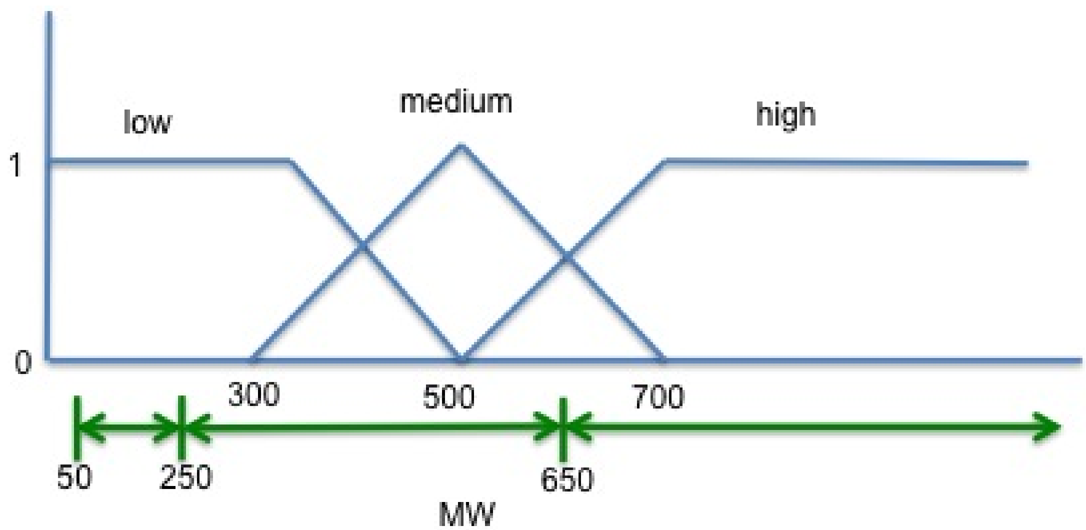

Figure 4.1. Fuzzy power membership function imposed with Rough Set boundary.

For the Rough Set, only medium-priority and high-priority rules are taken into consideration, so the input set to compare the Fuzzy model with Rough Set only incorporated values that fell into that range. The rule base has eight rules that produce medium priority and four rules that produce high priority. Among these twelve rules, four rules are tried with the two models in a random fashion. The results with input parameters are shown in Table 4.5. For all four inputs, the output from both the models was identical.

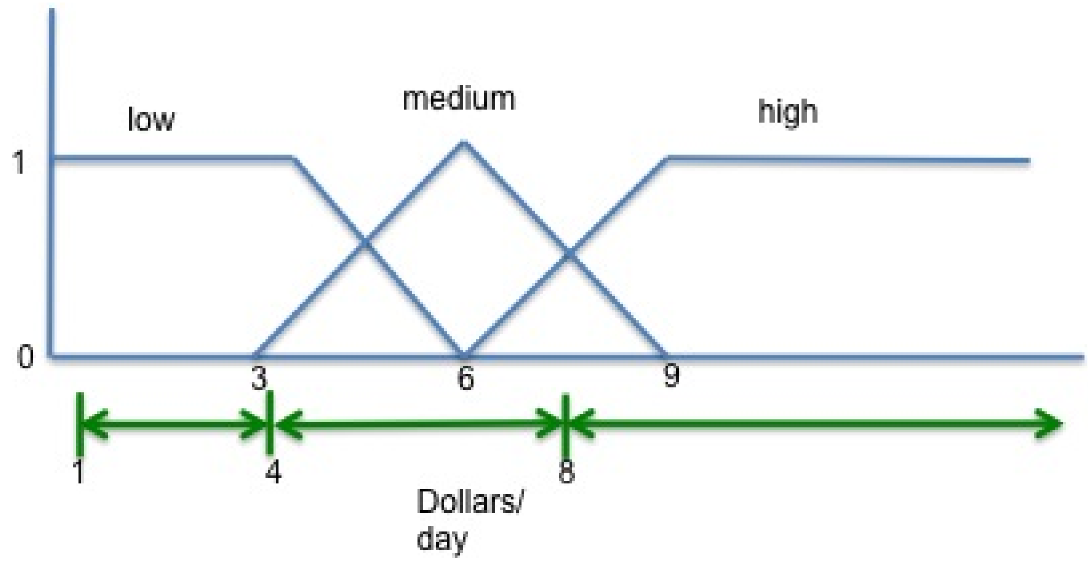

Figure 4.2. Fuzzy price membership function imposed with Rough Set boundary.

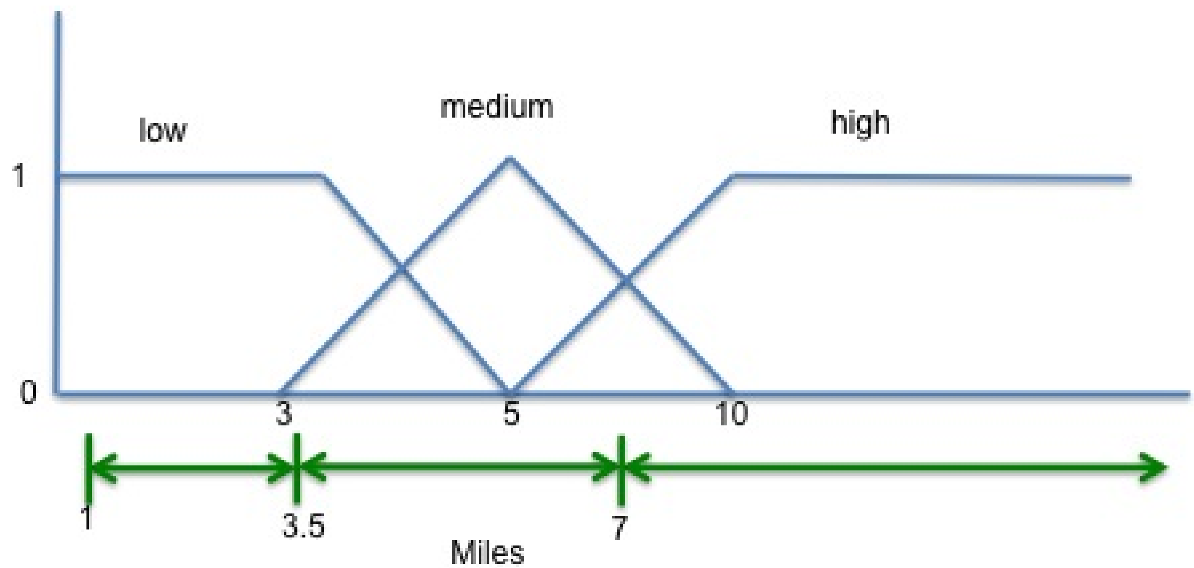

Figure 4.3. Fuzzy distance membership function imposed with Rough Set boundary.

Table 4.5. Test values for the Fuzzy and Rough Set comparison.

No.	Power(MW)	Price(Dollars)	Distance(Miles)	Fuzzy output	Rough Set output
1	600	2	12	Medium priority	12 (Med priority)
2	800	3	12	Medium priority	5 (Med priority)
3	800	3	2	High priority	1(High)
4	800	1	6	High priority	3(High)

Because the Rough Set model is more rigid than the Fuzzy model, the output from the Rough Set is taken in the form of rank, and then, the ranks are mapped to each priority level. For the Rough Set, ranks from 1 to 4 are high priority, and ranks of 4 to 12 are medium priority. The rank is shown in the table along with the priority level for each rank (inside parentheses). Both the Fuzzy and Rough Set approaches produced a similar result. However, for the Fuzzy model, the output was in the form of priority level, whereas the Rough Set was in the form of order. To produce an output decision, the Rough Set involved significantly less computation than the Fuzzy model. In practical terms, there could be scenarios where, for a specific input set, the Fuzzy model produces decisions in the same priority level. The Rough set model can then be used to pick or to process the output priority in a hierarchical fashion. Although the Rough Set is straightforward in producing output, it has a rigid boundary, so the output it produces does not take all the overlapping boundaries into consideration. Hence, as a standalone decision platform, the Rough Set may not produce the best decision. However, Fuzzy model can be integrated with Rough Set model to produce more fine grained decision outputs. In situations where Fuzzy produces identical priority values, the Rough Set rank output can be used to get the final output.

4.3. Routing Decision Output

Finally the model is tested to make routing decisions for a set of input values. The idea simulates a real-life condition when power failure has happened and routing decisions needs to be made within a short interval of time. For that interval of time, there are five sources available, and we need to find the best source out from these options. Each source has its coordinate location, amount of excess power on hand, and power-generation cost. On the demand side, we have the amount of demand power and coordinate locations for each substation or power transmission hub assigned to that locality. The model takes these parameters and, initially, calculates the distance out for each source-sink combination. Once the distance is calculated, the model will compute the priority value for each of source-sink combination. A typical input set is shown in Table 4.6. The attributes of each value are seen in Table 4.6.

Table 4.6. Test values for the routing decision in the Fuzzy model.

Price	Supply power	Supply(x)	Supply(y)	Demand power	Demand(x)	Demand (y)
3	700	203	400	350	201	396
4	750	100	200	450	100	201
7	500	105	203	300	104	205
2	550	102	202	250	98	198
6	470	99	198	285	105	204

Now, the model executes Fuzzy decision-making and assigns an output score to each source-sink combination. The output score consists of a priority level and a numeric value. Based on the priority and numeric score, the best source-sink combination can be found. The results are presented in Table 4.7. For a specific time interval t, the scores along the priority level will determine the best solution for resource allocation. The model collects demand power, demand location, supply power, supply location, and price of power generation for the time interval, t. Then it combines each demand and supply locations to produce the score.

Table 4.7. Fuzzy model output for the routing decision.

Supply power	Demand power	Priority	Score
700	450	medium	0.75
700	350	low	0.7360
700	300	low	1
700	285	low	1
700	250	low	1
750	450	medium	0.667
750	350	low	0.667
750	300	low	0.667
750	285	low	0.667
750	250	low	0.667
500	450	low	0.667
500	350	low	0.667
500	300	low	0.667
500	285	low	0.667
500	250	medium	0.75
550	450	medium	0.75
550	350	low	0.75
550	300	low	0.697
550	285	low	0.697
550	250	low	0.86
470	450	low	0.75
470	350	low	0.75
470	300	low	0.72
470	285	low	0.697
470	250	low	1

4.4. Complexity and Scalability

For any computational model, complexity and scalability are an important attributes. These two parameters define the potential applicability of any model. The time complexity of the Fuzzy models are in polynomial order. In our model, we have three break points: low, medium, and high. We also have three variables: power, price, and distance. The computations involved here is 3^3, the order is polynomial. When we compare this complexity with other mathematical models such as the Integer Linear Programming, we find that the Integer Linear Programming models are generally of exponential time-order complexity. We realize that the Fuzzy model is generally less computationally intensive than the Integer Linear Programming model. The production system Fuzzy model can be constructed with a low-order polynomial. The Fuzzy model would use significantly less amount of resources than the exponential time complexity of mathematical models.

In terms of scalability, the Fuzzy model will also has an advantage over the mathematical models. Fuzzy models are generally more scalable than mathematical-based models. Because, the Fuzzy model is less computationally intensive, it is usually more scalable. Hence, Fuzzy models can be used in a more distributed fashion than a mathematical models. Also, Fuzzy models have rule base, so validity in the context of numerical accuracy is not particularly applicable in this model. On the other hand, a mathematical model such as the Integer Linear Programming, it involves large matrices and high computations, so numerical accuracy and validity plays a crucial role in the model's overall accuracy and performance. For the same reason, the Fuzzy models are easier to implement than the mathematical-based models.

CHAPTER 5. CONCLUSION AND FUTURE WORK

There are some important lessons learned throughout the construction and implementation of the model. First, it can be learned that both of the Fuzzy and Rough Set model can be applied in the Smart Grid decision-making. Both the Fuzzy and the Rough set based models are fast in computation, so they can be used to filter out the best source-sink combination when a decision is crucial in terms of time. This kind of situations may arise when a sudden power failure has occurred due to a bad weather or any other unanticipated occurrences. The model would pick the best solution quickly in those situations. These models can also be applied in a distributed fashion because both the Fuzzy and Rough Set models are extremely scalable. In this way, the models can incorporate self-healing characteristic in the grid function. The time complexity is also in polynomial order compared to other mathematical models that generally have exponential-order complexity. Also, the models were straight forward and easy to implement.

Two alternative models are created for the Smart Grid resource-allocation problem. The principal purpose of the models is to connect power sources with appropriate sinks when considering the input parameters of power capacity, price, and distance. Fuzzy Logic and Rough Set are use to construct two models. When creating the Fuzzy model, the parameters and rule construction plays the most significant role. For the Fuzzy Logic model, the rule base has been constructed considering the operator's general knowledge, the operator's activity and the experience. From the rule base and the Inference Engine, the Fuzzy output has been defuzzified with the Mamdani Min Max approach. The Fuzzy model has the flexibility to make changes in the rule base at any time, so the rules can be updated if needed. The alternative model has been constructed using the Rough Set approach. For the Rough Set, the same rule base as of the Fuzzy is used. The identical rule base enables the comparison of the output. The Fuzzy model is tested with different input combinations chosen on a random basis. Because heuristic models are hard to test thoroughly, several probable scenarios are determined and the model output is collected for them. The model output is then verified with the domain knowledge and experience. The results are found to be satisfactory. The Fuzzy model output is compared with the Rough Set output. The results are found to be acceptable.

Several interesting observations were found in the model output. The Fuzzy model did not have any clear boundary for the price, power, and distance values, so the model output was largely dependent on the contributions from individual portions. As a result, the Fuzzy model outputs are more granular then the Rough Set model. The Rough Set model had a distinct boundary for each segment. Hence, a little change along the boundary value pushed the value into the next segment.

There are many areas where the current model can be extended. The membership functions chosen for the input are a combination of the triangular and trapezoidal functions. Other shapes, such as the bell shape, sigmoidal shape, etc., can also be tried to see the overall variation in the decision-making. One issue with Fuzzy Logic is that it cannot incorporate statistical data in a direct fashion. Historical data are incorporated in the form of rules. The power industry is highly statistics driven. There should have been some way to incorporate the decisions that are based on statistical findings. Currently, the only way to incorporate changes is to alter the rule base, and the change has to be done manually.

The other ways to change the Fuzzy model is to try with other defuzzification approaches such as the Center of Area. Different approaches for defuzzification may result in a better outcome from the model. Weight factor can also be assigned to each input parameters. Currently, all the power, price, and distance have similar weight. If we want to prioritize among each parameter, power would receive more priority than price and price would get more priority than distance. Then, a Takagi-Sugeno-Kant type model, as used by [30], can be utilized.

Learning is another attribute that can be incorporated into the current model. Adaptive Neuro Fuzzy Inference System (ANFIS) is one way that the current model can be extended to. In ANFIS, the learning is done with the incorporation of a neural network. The Fuzzy system is trained over time to become self-adaptive. Once the training is complete, the system is capable of making intelligent changes based on a neural network.

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