The Development Process and Design of a Hybrid Fuzzy Knowledge-Based System for Multiobjective Optimization of Power Distribution System Operations

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Abstract: A hybrid fuzzy knowledge-based system with crisp and fuzzy rules as well as numerical methods was developed for multiobjective optimization of power distribution system operations. The development process and knowledge acquisition process for the fuzzy knowledge-based system are described in detail. The fuzzy knowledge-based system has a four-level rule hierarchy. After a heuristic preprocessor proposes a list of switch openings that would seem to reduce system losses, network radiality rules consider whether to open a particular switch and find a corresponding switch that can be closed to maintain radiality. Network parameter rules determine if the proposed switching combination will violate network integrity. Network performance rules find the degree of desirability of proposed switching combinations for enhancing multiple objectives.

Keywords: distribution system optimization, distribution system reconfiguration, knowledge engineering, knowledge acquisition

1. Introduction

A hybrid fuzzy knowledge-based system was developed for multiobjective optimization of power distribution system operations. This provides a very powerful solution methodology by permitting the inclusion of both crisp and fuzzy rules as well as a coupling with numerical or algorithmic methods. The algorithmic methods provide updates to the system status through approximation formulas; these are internal to the knowledge base. Fuzzy logic is used to resolve multiple conflicting objectives, model soft constraints, and model expert knowledge of system behavior that cannot be quantified. This research paper will focus on the development process and overall design of the intelligent optimization system.

The hybrid fuzzy knowledge-based system effectively optimizes a power distribution network [1] for multiple system performance objectives:

- system loss reduction
- transformer load balancing
- reduction of transformer aging to decrease the failure rate and increase continuity of service
- maintenance of a satisfactory voltage profile throughout the network
- reactive power compensation
- conservative voltage reduction (CVR) practice to achieve peak shaving

The intelligent optimization system offers the following means of control:

- automated tie and sectionalizer switches
- transformer tap changers
- switched capacitor banks

The optimized network complies with a comprehensive list of constraints:

- network radiality
- line section and equipment capacity
- maintenance of acceptable fault current levels
- service priority for critical customers

2. Development of a Fuzzy Knowledge-Based System

The typical development process for a commercially viable fuzzy knowledge-based system is as follows [2]:

1. project selection
2. investigation
3. analysis
4. design specification
5. implementation
6. evaluation
7. monitoring
8. maintenance

The work described has traversed all stages of this framework up to and including the implementation. The evaluation, monitoring, and maintenance stages are performed once the fuzzy knowledge-based system has been integrated into a utility supervisory control and data acquisition (SCADA) system. Evaluation and monitoring are only possible once one analyzes the subtle characteristics of system performance.

Prior to describing the fuzzy rule base, the knowledge acquisition process is described to show the complexity of defining a knowledge base. The effectiveness of the knowledge-based application relies heavily on the successful conceptualization of rules.

3. Utility Knowledge Acquisition for a Fuzzy Knowledge-Based System

Knowledge acquisition and conceptualization are formidable tasks. For this reason, end users (that is, control room operators or plant personnel) should be actively involved in the development process and not merely employed as a source of knowledge. As operational personnel become more involved in the development of the fuzzy knowledge-based system, they will become more familiar with the type of information that must be recorded in the knowledge base. As the user interface on fuzzy knowledge-based system software tools becomes more user friendly, in-house development of a complex knowledge base will become feasible.

Having established that a proactive involvement of operational personnel is necessary, the engineer or knowledge-based system developer directs the knowledge acquisition process. Knowledge can be acquired from computerized data collection, formal or informal interviews and information collection sessions, or written questionnaires. Automated intelligent knowledge acquisition tools [3] have the ability to pose increasingly appropriate questions to build a better knowledge base. However, using these knowledge acquisition tools may not be justified to support a simple application that is to be implemented on a programmable logic controller (PLC). Written questionnaires permit inclusion of a larger number of people in the search process, but will yield considerable redundant information.

The interview process by the engineer should involve more than merely meeting with the expert in the confines of an office. The knowledge acquisition process should be performed at the site of the proposed fuzzy knowledge-based system. Interview subjects should be aware that this technology will not threaten their jobs, but rather permit them to perform daily tasks with increased ease and safety. It is important that the appropriate terminology is employed. As the fuzzy knowledge-based system is based primarily on qualitative descriptions, use of the proper vernacular will give any developments added credibility.

Fig. 1 shows the groups of people that must be involved in development of the knowledge base and how their expertise is employed in this process. The knowledge acquisition process starts with discussions with management to identify both written and unwritten objectives of the proposed fuzzy knowledge-based system development. Once the mandate of the development effort is understood beyond the scope of the written proposal, the engineer can direct the effort toward the desired goals. All personnel who may be familiar with the process or system behavior should be queried through some means. The dashed line in Fig. 1 symbolizes the fact that all operations, maintenance, engineering, and planning personnel of all levels of experience possess some type of expert knowledge and should be involved in the knowledge acquisition process. In the review process, the engineer finds the most applicable methods of knowledge acquisition. This review is an ongoing process until the fuzzy knowledge-based system is developed to the stage that it can be integrated into operations. After each revision of the knowledge acquisition process, the approach is modified to assure that knowledge is complete.

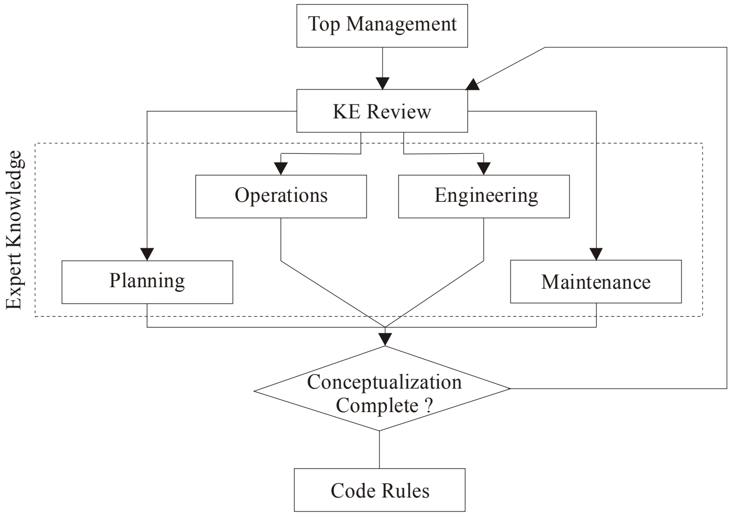

Fig. 1. People involved in knowledge conceptualization

Once a preliminary knowledge base has been acquired and processed, software implementation of the rules can proceed. Introduction of a preliminary prototype to potential users will yield further insight into system behavior. The development process never ceases. Once operations personnel are comfortable with the fuzzy knowledge-based system, it may be used, but maintenance will continually be required to account for changes in the system or operational practice. Prior to implementation, a rigorous validation procedure should be followed, as described in detail in [4].

The core of the multiobjective optimization system relies on a knowledge base determined from an expert appreciation for system behavior. While the subject of knowledge engineering may at first appear to be somewhat intuitive, identification and definition of a complete set of rules quickly becomes a formidable task. A structured knowledge acquisition procedure is essential to defining a knowledge base that accurately represents the network.

4. Structure of Hybrid Fuzzy Knowledge-Based System

The hybrid fuzzy knowledge-based system has a four-level rule hierarchy. Network radiality rules in the first level of the knowledge-based system are used in considering whether to open a particular switch. Network radiality rules in the second level are used in finding a corresponding initially open switch to close to assume the load transfer that would be necessitated by the switch opening. Network parameter rules in the third level of the knowledge-based system examine if switching combinations will violate network operational constraints. Network performance rules in the fourth level find the degree of desirability of proposed control operations for enhancement of multiple objectives.

A good starting point is obtained from a heuristic preprocessor based on network partitioning theory like that described in [5]. The good starting point is a list of switch openings that would seem to reduce total system losses. It is necessary for the hybrid fuzzy knowledge-based system to examine each member of the candidate list, identify if an associated switch can be closed to preserve radiality, and determine if this will improve the desired performance characteristics. If radiality can be maintained, then the network parameter rules are activated. If the network parameter rules find that the switching combination will not violate the operational integrity of the network, an assessment of performance enhancements can be made with the network performance rules. In the event that either the network radiality or operational constraints are violated, the switching combination is assessed to be unacceptable. After the load is transferred, numerical methods are used to update network parameters.

Regardless of the outcome of a candidate switching operation analysis, the subsequent recommended switch opening on the good starting point list is used. Once the list of candidate switches has been completely examined, the system performance is considered optimized. While determination of algorithm completion is based on examination of switching strategies, manipulation of switched capacitors and transformer tap changers is performed within the rules. A summary of the heuristic rules in the hybrid knowledge-based system follows. The extremely powerful FuzzyCLIPS language [6] was used in the development of the fuzzy knowledge base.

5. Fuzzy Antecedents

Fuzzy variables are defined to describe the following inputs or antecedents:

- Recent temperature trend
- Line section loading
- Transformer aging
- Voltage level guidelines

In the interest of brevity, only the transformer aging antecedent is defined here.

The fuzzy membership functions for the transformer aging variable are shown in Fig. 2.

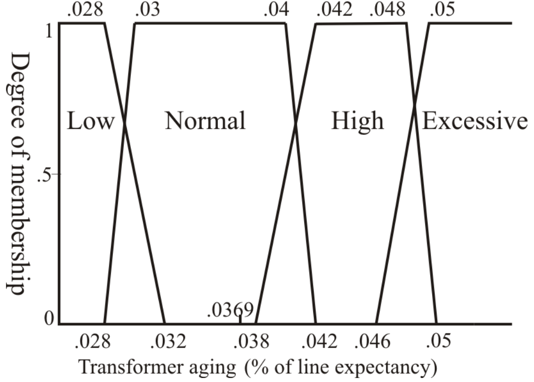

Fig. 2. Transformer Aging

The following linguistic qualifiers are used:

- *Normal*
- *Low*
- *High*
- *Excessive*

Normal Aging: The qualitative description of *Normal* is centered about the maximum daily recommended operating limit: 0.0369% for a power transformer with rating between 500 kVA and 100 MVA. Based on discussions with utility engineers, it is apparent that aging rarely meets the maximum allowable value, so *Normal* is limited to approximately 110% of the maximum amount. A trapezoidal function is employed for this linguistic qualifier.

Low Aging: The *Low* aging qualifier, represented by a Z-shaped function, is the region in which the transformer typically ages. This qualifier is designated as *Low* to match the terminology expressed in the standards. *Low* aging occurs for values less than 80% of the daily recommended amount. A utility's desire to preserve transformers for longer than the period identified in the standards is reflected in the definition of rules, which tend to favor *Low* aging.

High Aging: High aging is defined as a very narrow region in which operation is only permitted during emergency conditions. Beyond a daily aging of 130% of the daily recommended maximum, it is believed that the risk of excessive aging is far too great to permit operation. A trapezoidal function is employed for this linguistic qualifier.

Excessive Aging: Excessive aging, represented by an S-shaped function, is employed to decisively eliminate an operation that loads a transformer beyond the 130% threshold. Aging to the *High* or *Excessive* level will most probably violate the capacity of some piece of line equipment. The operation would likely be deemed *Undesirable* (defined later) for other criteria prior to the activation of transformer aging heuristics.

6. Fuzzy Consequents: A Standardized Degree of Desirability

All fuzzy variables that describe an outcome or consequent use the same fuzzy sets called the standardized degree of desirability. By using the same fuzzy sets, there is an effective means of comparison when aggregating the results to obtain a single description of the desirability of the solution. This is particularly important when trying to resolve multiple conflicting objectives.

In fuzzy rules, the outcome or consequent is described by a standardized degree of desirability that is arbitrarily defined. For those rules in which the fuzzy set represents a physical quantity, membership function definition is not arbitrarily assigned. By assigning a different scaling factor to the membership function describing the degree of desirability of a particular rule, either higher or lower preference can be given to optimizing a particular objective. If all outcomes were assigned the same degree of desirability, then all objectives would have equal preference. Following implementation in a utility, it may be necessary to calibrate fuzzy membership functions describing the degree of desirability to ensure that utility objectives are assigned the desired order of preference.

Fig. 3 shows fuzzy sets for different degrees of desirability of a consequent.

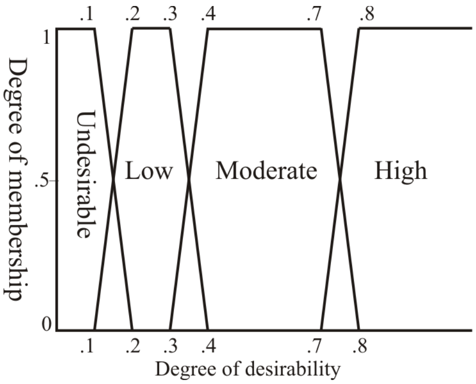

Fig. 3. Standardized Degree of Desirability

The following linguistic qualifiers expressing the degree of desirability are employed:

- *Moderate*
- *Undesirable*
- *Low*
- *High*

Moderate Desirability: As shown in Fig. 3, *Moderate* is defined to have a degree of membership of 1 over the domain of 0.4 through 0.7. *Moderate* has the largest range of values to assure greater conservatism in the solution strategy. In the subsequent definition of the fuzzy rules, the outcome will lie within the *Moderate* region in most cases. A *Moderate* assessment indicates that a switching combination will neither violate network integrity nor enhance a performance objective for network parameter and performance heuristics.

Undesirable: Undesirable is represented by a Z-shaped membership function and has a degree of membership of 1 over the domain of 0 through 0.1. Only *Undesirable,* not *Low,* indicates that an operation is unacceptable. In the case of network parameter rules, an *Undesirable* assessment indicates that the proposed operation violates network integrity and should not be pursued further. For network performance rules, an *Undesirable* outcome indicates that one of the performance objectives is seriously degraded and the operation should not be considered.

Low Desirability: Low is represented by a trapezoidal fuzzy set like *Moderate,* but its domain is much smaller. Having a degree of membership of 1 over the domain of 0.2 through 0.3, it is apparent that outcomes within this region are thought to occur over a smaller domain space. *Low* desirability does not indicate that an option is clearly undesirable, but rather that the option may not have as high of a degree of desirability as would be expected with respect to the objective in question. For network parameter rules, *Low* indicates that a large operational margin will no longer exist, but operation in that region remains viable. For network performance rules, this outcome means that an objective may not be improved or may even be slightly compromised, but there will be no serious adverse effects.

High Desirability: High is represented by an S-shaped membership function and has a degree of membership of 1 over the domain of 0.8 through 1.0. The *High* assessment applies in situations where the indices very clearly identify a favorable condition. In the case of network parameter rules, it is very clear that network integrity will not be violated and a large operational margin exists. For network performance rules, a *High* outcome indicates that performance objectives will be substantially improved by the proposed control action.

7. Network Radiality Rules

Network radiality heuristics identify a pair of switching operations that will preserve radiality. A branch exchange is performed in which opening one line section results in the closing of another. A branch exchange can be somewhat inefficient in terms of solution time if not initialized by a good starting point, but can be employed in knowledge-based methods. The network radiality heuristics are described in detail in [7, 8].

8. Network Parameter Rules

Heuristic 3.1: Ensure Acceptable Fault Current Levels

If switching operation includes existing switches, then fault current level remains acceptable.

Heuristic 3.2: Line Section Capacity

If line section loading is *Excessive,* then switching combination is *Undesirable;*

If emergency condition and line section loading is *Low, Normal,* or *High,* then switching combination has *High* desirability;

If temperature trend is *Cold* and line section loading is *Low* or *Normal,* then switching combination has *High* desirability;

If temperature trend is *Cold* and line section loading is *High,* then switching combination has *Low* desirability;

If temperature trend is *Normal* or *Hot* and line section loading is *Low,* then switching combination has *High* desirability;

If temperature trend is *Normal* or *Hot* and line section loading is *Normal,* then switching combination has *Moderate* desirability;

If temperature trend is *Normal* or *Hot* and line section loading is *High,* then switching combination is *Undesirable.*

Heuristic 3.3: Equipment Capacity

While the fuzzy membership functions representing line section conductors or equipment loading are different, identical guidelines are employed to define the loading limits of other line section and equipment types. The fuzzified rules are identical and the linguistic qualifiers associated with different loading conditions are identical for all types of line sections and equipment. For this reason, it is only necessary to provide one set of rules above.

Heuristic 3.4: Transformer Aging Due to Temporary Transformer Overloading

If temporary transformer overload and transformer aging is *Low,* then switching combination has *High* desirability;

If temporary transformer overload and transformer aging is *Normal,* then switching combination has *Moderate* desirability;

If emergency condition and temporary transformer overload and transformer aging is *High,* then switching combination has *Moderate* desirability;

If temporary transformer overload and transformer aging is *Excessive,* then switching combination is *Undesirable.*

Heuristic 3.5: Daily Transformer Aging

If transformer aging is *Low,* then switching combination has *High* desirability;

If transformer aging is *Normal,* then switching combination has *Moderate* desirability;

If transformer aging is *High,* then switching combination has *Low* desirability;

If transformer aging is *Excessive,* then switching combination is *Undesirable.*

Heuristic 3.6: Minimum Voltage Requirements

A voltage update routine is employed that either steps up the transformer taps for voltage correction or steps down the transformer taps for CVR until the desired objective is attained. Bus voltages are updated using the ladder network technique.

If voltage level is *Unacceptable* or *Emergency,* then invoke voltage update routine;

If voltage level is *Overvoltage,* then invoke voltage update routine with CVR policy set;

If voltage update routine executed and voltage level is *Range B,* then switching combination has *Moderate* desirability;

If voltage update routine executed and voltage level is *Range A,* then switching combination has *High* desirability;

If voltage update routine executed and emergency condition and voltage level is *Emergency,* then switching combination has *Moderate* desirability;

If voltage update routine executed and normal condition and voltage level is *Emergency* or *Unacceptable,* then switching combination is *Undesirable.*

Heuristic 3.7: Adjustment of Reactive Power Compensation

If load is transferred to substation and main feeder is equipped with switched capacitors, then switch in capacitors according to 2/3 rule;

If load is shed by substation and main feeder is equipped with switched capacitors, then switch out capacitors according to 2/3 rule.

Heuristic 3.8: Service Priority

If priority customer supplied by several service entrances, then customer is to be supplied by two different utility substations.

9. Network Performance Rules

Following the successful completion of network radiality and parameter heuristics, network performance heuristics are activated. Network performance heuristics assess the capability of a proposed switching operation to optimize specific objectives. If either network radiality or operational parameters are violated in the lower two levels of the rule hierarchy, then the switching option is rejected. For network performance rules, the consequents will not automatically cause a candidate option to be eliminated. When assessing the performance of proposed network modifications, the integrity of the network has already been assured; consequently, even modest improvements in service can be accepted. To offer a standard basis of comparison, all network performance heuristics except Rule 4.2 use the standardized degree of desirability to express the benefit of the outcome.

Heuristic 4.1: Loss Reduction Assessment through Voltage Drop (the heuristic of Civanlar et al [9])

If $\Delta v_{sub\ 1\text{-}a} > \Delta v_{sub\ 2\text{-}b}$, then transfer of bus A to substation 2 has *Moderate* desirability;

If $\Delta v_{sub\ 1\text{-}a} > \Delta v_{sub\ 2\text{-}b}$, then transfer of bus A to substation 2 is *Undesirable.*

where:

bus A is connected to substation 1; bus B is connected to substation 2;

$\Delta v_{sub1\text{-}a}$ is voltage drop from substation 1 to bus A;

$\Delta v_{sub2\text{-}b}$ is voltage drop from substation 2 to bus B.

Heuristic 4.2: Conservative Voltage Reduction (CVR)

The voltage level is lowered while maintaining a reasonable quality of service to customers. For CVR operation, tap changers lower the voltage level until it is slightly higher than the lower region of the tolerable zone. If the voltage at the transfer point or voltage critical bus lies within the favorable zone, then the voltage update routine is invoked to lower tap settings until the voltage is in the tolerable zone. If the voltage is already in the tolerable zone, CVR operation will not be performed. These voltage levels are based on ANSI loading guidelines [10].

If voltage level is *Range A* or *Overvoltage* and system status is not emergency, then invoke voltage update routine with CVR option.

Heuristic 4.3: Heuristic Indices (Sarfi et al [11])

Sarfi et al defined two heuristic indices [11] that calculated the desirability of a switching operation based on voltage, power flow, and impedance parameters from both the open and closed switches of the switching pair. Indices C_1 and C_2 represent the most desirable and least desirable switching operations, respectively. An index value of 0 identifies an undesirable switching operation. An index value of 1 identifies the most desirable switching operation.

If $C_1 < 0.25$, then switching combination is *Undesirable;*

If $C_2 > 0.75$, then switching combination has *Moderate* desirability.

Heuristic 4.4: Overall System Loss Reduction

If aggregated assessment of losses is *Low, Moderate,* or *High,* then losses reduced with the degree of desirability of the aggregated loss assessment and candidate switching combination is accepted;

If aggregated assessment of losses is *Undesirable,* then losses reduced with the degree of desirability of the aggregated loss assessment and candidate switching combination is not accepted.

Heuristic 4.5: Conversion Criteria

If aggregated assessment of losses is *Moderate* or *High* and all network radiality and network parameter rules are satisfied, then losses reduced with the degree of desirability of the aggregated loss assessment and overall system optimization procedure is accepted;

If aggregated assessment of losses is *Unacceptable* or *Low,* then losses reduced with the degree of desirability of the aggregated loss assessment and overall system optimization procedure is not accepted.

If all system constraints are satisfied and the reduction in losses is at least *Moderate* in desirability, then the proposed system changes are validated by conducting a load flow analysis to ensure network integrity is not violated. This validation is a redundant measure for greater reliability, and a utility may choose to bypass the validation to reduce solution time.

10. Validation and Simulations

The intelligent optimization system was validated and simulated on a subsystem of an actual 4.4 kV radial distribution network with approximately 70 load points including 14 major customers of the commercial, industrial, or multiunit residential types. The network was supplied by two substations, each equipped with an identical 5 MVA transformer. The network was equipped with 31 switches of which 20 were to be employed in the system optimization method. An extensive validation of the intelligent optimization system during the time of highest system demand on the test network indicated that system constraints were never violated by the optimization system software and all performance characteristics were enhanced. There was an improved voltage profile, reduced line section loading, and diminished transformer aging.

Extensive simulations were performed covering operation of the power distribution system over a year including summer weekdays, summer weekends/holidays, winter weekdays, and winter weekends/holidays. Residential, commercial, industrial, and mixed load types were represented in the simulations. Simulations showed that the optimization of power distribution system operations can be significantly enhanced through the use of automated tie and sectionalizer switches, transformer tap changers, and switched capacitor banks. Simulations further revealed that optimization solutions are found in a time-efficient manner while significantly enhancing performance, achieving all objectives, and producing significant monetary savings.

11. Conclusion

After a heuristic preprocessor identifies several switch openings that would reduce system losses, network radiality and parameter heuristics identify those switch closures that would preserve radiality and system operational criteria, respectively. Network performance heuristics assess the capability of a proposed operation to optimize specific objectives. Both qualitative and quantitative rules are included in the proposed system optimization technique to ensure that proposed system changes will not compromise the integrity of the network or violate principles of sound engineering practice. All operational aspects of power distribution systems have been considered in the proposed system optimization method and a solution is still obtained in real time. Another distinct advantage associated with this synergetic performance optimization method is that no aspect of system performance will be worsened under any circumstances.

These optimization methods based on the synergy of knowledge-based and numerical methods can decrease system energy losses, thus resulting in a more energy efficient system and less burning of non-renewable fossil fuels (coal, oil, and natural gas) to generate electricity. Less burning of fossil fuels leads to reduced global warming [12], decreased air pollution and acid rain, diminished dependence on foreign oil, and reduced harm to the environment and wildlife from obtaining fossil fuels. Reduced global warming elicits diminished severity of natural disasters caused by global warming, less extreme weather, diminished spread of infectious diseases, and less loss of life. Decreased air pollution and acid rain induce fewer health problems, less harm to plant and aquatic life, and reduced damage of materials. Diminished dependence on foreign oil reduces skewing and inequities in foreign policy. In nuclear power plants, there would be diminished uranium consumption and hence less nuclear waste. Furthermore, the methods described can increase transformer life spans and enhance the reliability of a power distribution network. This can prevent power outages, which cost individuals and organizations tremendous productivity, time, and money. Decreased consumption of fossil fuels or uranium and increased transformer life spans lower operating costs and consumer prices.

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