AI Magazine Volume 27 Number 3 (2006) (© AAAI)

Intelligent Multiobjective Optimization of Distribution System Operations

Robert J. Sarfi and Ashu M. G. Solo

■ 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 operation. The development process and knowledge-acquisition process for the fuzzy knowledge-based system are described in detail. Fuzzy sets are defined for recent temperature trend, line section loading, transformer aging, voltage-level guidelines, and the degree of desirability of a proposed switching combination. 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 whether the proposed switching combination will violate network integrity. Network performance rules find the degree of desirability of proposed switching combinations for enhancing multiple objectives. All operational aspects of power distribution systems are considered, and a solution is still found in real time.

A hybrid fuzzy knowledge-based system was developed for multiobjective optimization of power distribution system operation (Gonen 1985). This system 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 (Gupta, Jin, and Homma 2003) is used to resolve multiple conflicting objectives, model soft constraints, and model expert knowledge of system behavior that cannot be quantified. This article will focus on the development process and overall design of the intelligent optimization system.

Certainty and precision have much too often become an absolute design requirement in engineering problems. The excess of precision and certainty in engineering and scientific research and development often provides unrealizable solutions. Fuzzy logic, based on the notion of relative graded membership, can deal with information that is uncertain, imprecise, vague, or without sharp boundaries. Fuzzy logic allows for the inclusion of vague human operator assessments (Sarfi and Solo 2002a). Also, it provides a means for conflict resolution of multiple criteria and better assessment of options. This leads to greater adaptability, tractability, robustness, a lower cost solution, and better rapport with reality in the development of intelligent systems for decision making, identification, recognition, optimization, and control.

The tolerance of imprecision and uncertainty in fuzzy logic can be effectively used in intelligent optimization of power distribution system operation (Sarfi and Solo 2005a). However,

Sarfi, Salama, and Chikhani (1994a) as well as Sarfi and Solo (2002c) demonstrate that fuzzy logic is not an asset in all power systems planning and operation scenarios. Some rules do not involve any uncertainty or can be represented better without fuzzy generalizations. Every application must be thoroughly reviewed to ensure that the best methods are employed.

Knowledge-based or numerical methods can be used in optimization of power distribution system operation. An extensive study of software tools used in real-time power system applications concluded that electric utility companies were not satisfied with conventional approaches based on numerical methods in 50 percent of the cases examined (Sarfi, Salama, and Chikhani 1994a). Dissatisfied parties cited two major shortcomings in techniques based on numerical methods: (1) lack of flexibility in system modeling, and (2) exclusion of operators' input in the decision-making process. While algorithmic numerical methods will generally offer superior system-optimization results, their solution times are often excessive. The algorithmic model may not include crucial system-dependent information that can be described only with linguistic rules.

Knowledge-based methods are an efficient means of optimizing power distribution system performance (Sarfi, Salema, and Chikhani 1994a and Sarfi, Salama, and Chikhani 1996a. A knowledge-based method offers the advantage that it employs heuristic and factual information derived from knowledge of the system behavior. From an engineering perspective, the integration of heuristic rules into the proposed reconfiguration method bridges the gap between abstract theory and an industrially viable tool. However, there is a serious shortcoming of knowledge-based methods in an application such as optimization of power distribution system operation. An exhaustive search procedure such as a branch-and-bound strategy is typically employed to obtain a solution. An exhaustive search procedure to optimize performance of even a small distribution network would require a considerable amount of time. System-optimization techniques based solely on knowledge-based methods suffer from numerous shortcomings: examination of branch exchange is fast but will most likely offer only a poor local optimum, and efforts to retain a radial network may limit the permutations and combinations of switching operations that can be considered.

Through a coupling of knowledge-based and numerical methods (Sarfi and Solo 2005b), the shortcomings of the individual techniques are overcome. A hybrid fuzzy knowledge-based system with a coupling between knowledge-based and numerical methods combines the advantages of both methods for multiobjective optimization of power distribution system operation. In addition to including existing numerical methods, it embodies all existing qualitative knowledge of the system. One must wonder why the hybrid fuzzy knowledge-based system is not more widespread in industry.

The hybrid fuzzy knowledge-based system effectively optimizes a power distribution network for multiple system-performance objectives, including 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, and conservative voltage reduction (CVR) practice to achieve peak shaving.

The intelligent optimization system offers several means of control: automated tie and sectionalizer switches, transformer tap changers, and 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, and service priority for critical customers.

Development of a Fuzzy Knowledge-Based System

The typical development process for a commercially viable fuzzy knowledge-based system is as follows (Millington 1981): (1) project selection, (2) investigation, (3) analysis, (4) design specification, (5) implementation, (6) evaluation, (7) monitoring, and (8) maintenance. The work described has traversed all stages of this framework up to and including the implementation. Evaluation and monitoring are only possible once one analyzes the subtle characteristics of system performance. Prior to describing the fuzzy knowledge-based system, 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.

Utility Knowledge Acquisition for a Fuzzy Knowledge-Based System

Knowledge acquisition and conceptualization are formidable tasks. For this reason, end users (that is, distribution operators or plant person-

nel) 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 (Clancy 1985) have the ability to pose increasingly appropriate questions to build a better knowledge base. 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.

Figure 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 figure 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.

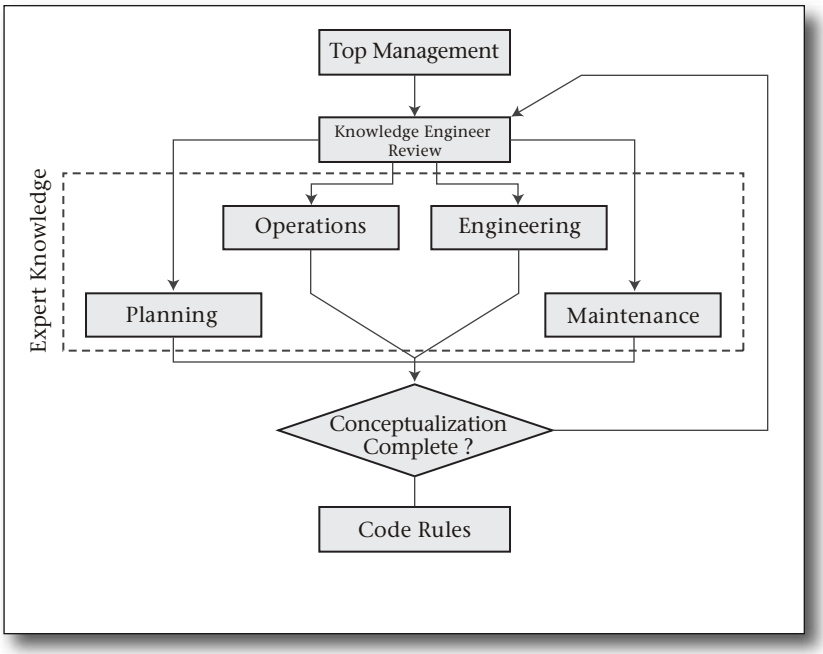

Figure 1. People Involved in Knowledge Conceptualization.

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 Gupta (1991).

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.

Structure of a Hybrid Fuzzy Knowledge-Based System

A good starting point is obtained from a heuristic preprocessor based on network partitioning theory like that described in Sarfi, Salama, and Chikhani (1996b) and Sarfi et al. (1993). The good starting point is a list of switch openings that would seem to reduce total system losses. The hybrid fuzzy knowledge-based system has a four-level rule hierarchy. Network radiality rules in the first level are used in considering whether to open a particular switch. If a switch can be opened, then network radiality rules in the second level of the hybrid fuzzy knowledge-based system are used in finding a corresponding initially open switch to close to assume the load transfer that would be necessitated by the switch opening. If there is a switching combination that will preserve radiality, then network parameter rules in the third level of the hybrid fuzzy knowledge-based system examine whether the switching combination will violate network operational constraints. If the operational integrity of the network will not be violated by the switching combination, then network performance rules in the fourth level find the degree of desirability of proposed control operations for enhancement of multiple objectives.

Regardless of the outcome of a candidate switching-operation analysis, the subsequent recommended switch opening on the good starting point list is examined. After the load is transferred, numerical methods are used to update network parameters. 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.

The heuristic rules in the hybrid fuzzy knowledge-based system are summarized later. Where there is a coupling between knowledge-based and numerical methods, the integration of numerical methods is described. The network radiality rules are described in greater detail in Solo and Sarfi (2005b). Network parameter rules are described in greater detail in Sarfi and Solo (2002c) as well as Sarfi and Solo (2006). Network performance rules are described in greater detail in Sarfi and Solo (2002c). The extremely powerful FuzzyCLIPS language (Orchard 2004) was used in the development of the fuzzy knowledge-based system.

Fuzzy Set Definition

Fuzzy sets that describe fuzzy variables are represented by trapezoidal, Z-, and S-shaped membership functions. Z- and S-shaped functions assign a membership value to all possible fuzzy domain values, even those below the lower limit and above the upper limit. The nonlinear Π function is perhaps the most logical parallel to the human thought process, but the linear trapezoidal membership function is an accepted compromise (Sarfi, Salama, and Chikhani 1996a). A linear function such as the trapezoidal function reduces solution time considerably and is a good piecewise linearization of the Π function. It is our belief that the normalcy condition should be employed as the basis for any membership function definition, as it is best understood. In the fuzzy variables defined later, *normal* or *moderate* is represented by a trapezoidal membership function.

Linguistic qualifiers by themselves can be restrictive in describing fuzzy variables, so linguistic hedges are used to supplement linguistic qualifiers through numeric transformation. For example, a *very* hedge can square the initial degree of membership μ in a fuzzy set:

$$\mu_{\text{very } high}(T) = [\mu_{high}(T)]^2.$$

These other standard linguistic hedges (Orchard 2004), which accurately model the human reasoning process, are used too: *not, somewhat, more or less, extremely, above,* and *below.* Linguistic qualifiers and hedges are interpreted with the FuzzyCLIPS language (Orchard 2004).

Fuzzy Antecedents

Fuzzy variables are defined to describe the following inputs or antecedents: (1) recent temperature trend, (2) line section loading, (3) transformer aging, and (4) voltage-level guidelines.

Recent Temperature Trend

Fuzzy logic is employed to describe short-term temperature trends. For the fuzzy sets describing temperature to maintain some physical significance, seasonal average temperature is used as a characteristic value. While historical temperature information is logged by distribution operators for peak forecasting, it is more appropriate to represent recent trends in temperature deviation from the seasonal average by a linguistic qualifier: *normal, cold, or hot.*

Ambient and ground temperature affect the capacity of equipment. Lower temperatures permit higher loading. An example of the fuzzy set definition of temperature for winter condi-

tions is shown in figure 2. Once implemented by a utility, it may be necessary to calibrate the membership function parameters to best approximate system behavior.

Normal Temperature Trend. A fuzzy set modeling *normal* temperature trends should be based on the seasonal average for the geographic region. The trapezoidal membership function is chosen to represent *normal* temperature trends for the winter season. Unity membership occurs in the domain of –5°C to 13°C. There is a small overlap in *normal* with *cold* and *hot*. Overlap in fuzzy sets shows imprecise knowledge of the temperature, but it is reasonable to interpret temperature variation in this manner, as an operator would report trends in ambient atmospheric temperature. The temperature range of *normal* corresponds to that which is considered a normal operating temperature. The fuzzy set provides a range of possible temperatures to overcome any inconsistencies in the temperatures throughout the system. Membership function bounds for *cold* and *hot* are selected based on the definition of *normal*.

Cold Temperature Trend. The *cold* function is modeled with a Z-shaped fuzzy membership function. *Cold* decreases from a membership value of 1 to 0 with slope $m = -0.5$ and *normal* increases from 0 to 1 with slope $m = 1$. The magnitude of the slope of the leading edge of *normal* is greater than the magnitude of the slope of the trailing edge of *cold*. This biases membership toward the *normal* set. This membership bias contributes to a conservative line-loading policy, as line sections can tolerate less loading at higher temperatures. *Cold* has a unity degree of membership for temperatures less than –6°C.

Hot Temperature Trend: Hot is modeled with an S-shaped fuzzy membership function so no upper bound is assigned. As *normal* decreases from 1 to 0 with slope $m = -0.5$, *hot* increases in membership with slope $m = 1$. Membership is biased toward the *hot* set, thereby contributing to a conservative line-loading policy. It is our belief that from an operational perspective, it is desirable to err within a safe operating zone. *Hot* has a unity degree of membership for temperatures greater than 14°C.

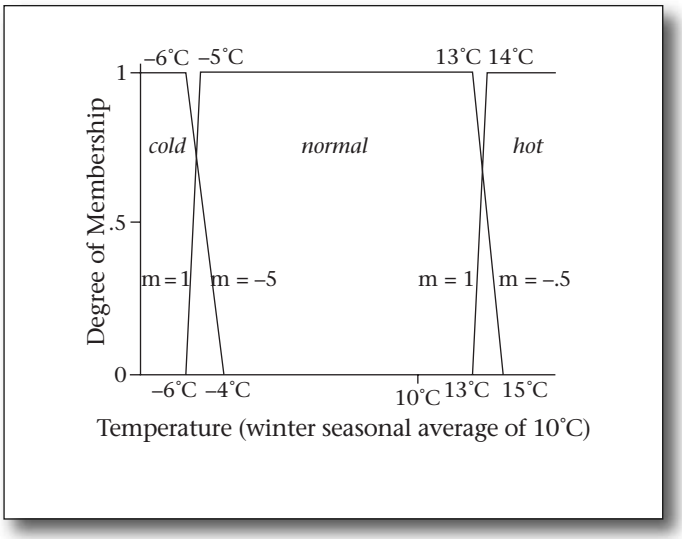

Figure 2. Recent Temporature Trend.

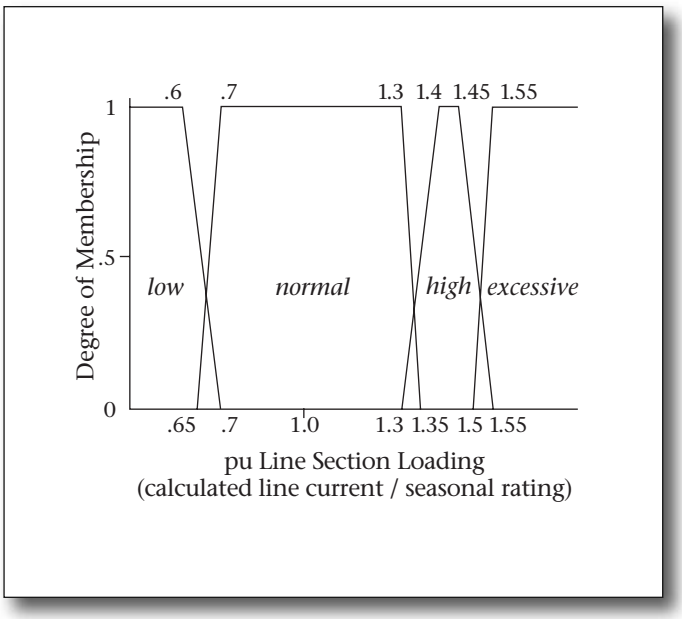

Figure 3. Line Section Loading.

Line Section Loading

Figure 3 shows the fuzzy membership functions that represent line section loading for a sample system. The pu loading is determined by taking the quotient of the calculated line section current and the seasonal rating of the line section. The linguistic qualifiers associated with line section loading are as follows: *normal, low, high, and excessive*.

Normal Loading: In figure 3, the line section loading of 1.0 pu corresponds to loading at the recommended seasonal limit. Under *normal* operating conditions, a utility will load line sections to 133 percent (1.33 pu) of the line section's thermal limits; this widely accepted operational practice is based on utility experience. It is our belief that the lower bound on *normal* loading should be approximately 65 percent (0.65 pu) of the equipment rating. Therefore, the *normal* fuzzy set has unity membership in the domain of 0.7 pu to 1.3 pu. The distribution network should normally operate within this domain.

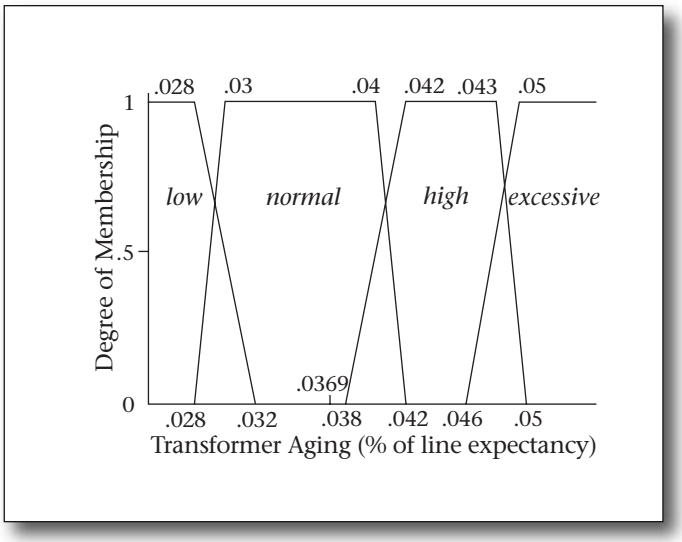

Figure 4. Transformer Aging.

Low Loading: Low line section loading identifies conditions when line section current is well below what is normally witnessed. *Low* is represented by a Z-shaped function; this is the standard type of function used for representing lower operating regions. Membership function slopes are selected to bias membership toward the *normal* set over the *low* set, thus ensuring a conservative loading policy. A unity degree of membership occurs for every pu loading less than 0.6.

High Loading: When seasonal temperature is well below average, loading guidelines can be somewhat relaxed; the *high* fuzzy membership function applies to such situations. The magnitude of the slope of the leading edge of *high* is less than the magnitude of the slope of the trailing edge of *normal*. The selection of slopes in this manner biases the inference process slightly toward the *normal* condition. This is permissible because the loading guidelines permit operation to 133 percent, but the *normal* fuzzy set has been defined so that unity membership stops at 130 percent. A *high* condition is only permitted for loading slightly higher than the 1.3 pu limit imposed on *normal*. For this reason, there is a unity degree of membership only from 1.4–1.45 pu.

Excessive Loading: Excessive line section loading is considered unacceptable under any circumstances. Operation in excess of 155 percent of equipment rating is considered unsafe. *Excessive* is represented by an S-shaped function to ensure that loadings greater than 155 percent belong to this fuzzy set. The magnitude of the slope of the leading edge of *excessive* is greater than the magnitude of the slope of the trailing edge of *high*. This ensures that membership in this domain is biased toward *excessive* to enforce conservative loading policy.

Transformer Aging

The fuzzy membership functions for the transformer aging variable are shown in figure 4. The following linguistic qualifiers are used: *normal, low, high, and excessive.*

Normal Aging: The qualitative description of *normal* is centered about the maximum daily recommended operating limit: 0.0369 percent for a power transformer with rating between 500 kVA and 100 MVA.[1] Based on discussions with utility engineers, it is apparent that aging rarely meets the maximum allowable value, so *normal* is limited to approximately 110 percent of the maximum amount.

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 percent 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 is defined as a very narrow region in which operation is permitted only during emergency conditions. Beyond a daily aging of 130 percent 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 percent 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.

Voltage-Level Guidelines

The voltage level is fuzzified in accordance with the membership functions described in figure 5. The following linguistic qualifiers are defined to represent the voltage-level domains: *unacceptable, emergency, range B (tolerable zone), range A (favorable zone), and overvoltage.*

All slopes of membership functions are selected to draw voltage assessments into the lower voltage range. This is necessary for a conservative voltage policy, thus assuring a quality supply.

The *range A, range B,* and *emergency* voltage levels are based on ANSI loading guidelines.[2] Utility operation is typically in the domain of either *range A* or *range B*. While operation in *range A* is certainly more favorable, no adverse effects will result from operation in *range B*. No operational constraints are placed on a utility by the standards when operating in *range B*. The fuzzy sets describing these conditions are based on guidelines established within the standards: *Range A* is from 96–110 percent of nominal voltage, and *range B* is roughly from 90–95 percent. Operation in the *emergency* domain is permitted only during emergency conditions for a short time. The *emergency* region lies between 80–90 percent of nominal voltage.

ANSI standards do not define *unacceptable* and *overvoltage* conditions, as operation within these regions is not permissible. *Unacceptable* is represented by a *Z*-shaped membership function so all voltages below the *unacceptable* region are identified as *undesirable* (defined later). *Overvoltage* conditions are unlikely to occur, particularly if a conservative voltage-reduction (CVR) policy is practiced. The parameters of the *overvoltage* condition are selected to ensure that any voltages greater than *range A* values are deemed *undesirable*.

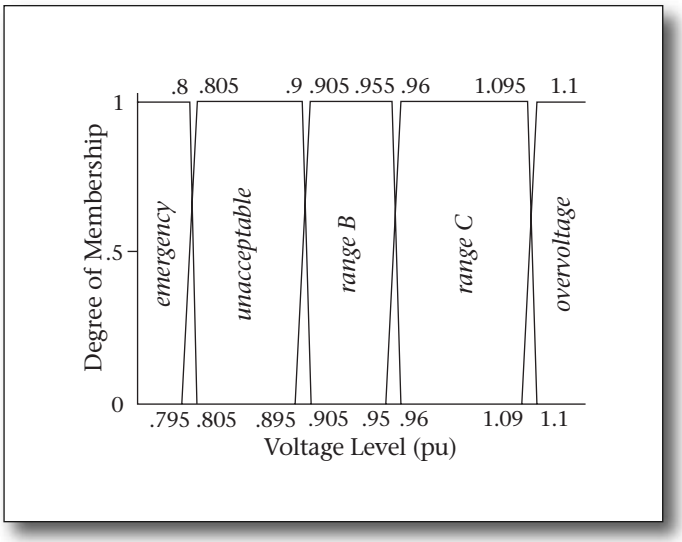

Figure 5. Voltage Level Guidelines.

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.

Figure 6 shows fuzzy sets for different degrees of desirability of a consequent. The following linguistic qualifiers expressing the degree of desirability are employed: *moderate, undesirable, low, and high.*

Moderate Desirability: As shown in figure 6, *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

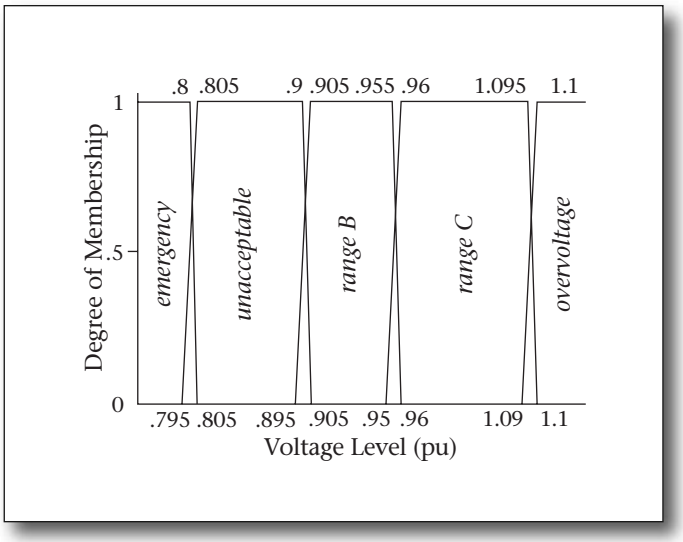

Figure 6. Standardized Degree of Desirability.

rather that the option may not have as high 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.

Network Radiality Rules for Opening an Initially Closed Switch

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 radiality rules are entirely crisp in nature. Switch status is a binary variable; it is either open or closed, so there is no uncertainty associated with the status of switches that are employed in switching operations being analyzed. Also, there is no fuzziness about the outcome of a proposed switching combination; the proposed configuration is either radial or not radial. Therefore network radiality heuristics are not suited to fuzzification because of the crisp nature of their function.

Heuristic 1.1: Line Section Previously Switched during an Interval in Distribution System Optimization. If the line section was previously switched in distribution system optimization during an interval, then the line section is not a candidate to open.

Heuristic 1.2: Source Line Section. If the line section is a source line section, then the line section is not a candidate to open.

Heuristic 1.3: Terminal Line Section. If the line section is a terminal line section, then the line section is not a candidate to open.

Heuristic 1.4: Intermediate Line Section with No Switch. If the line section is an intermediate line section and does not have a switch, then the line section is not a candidate to open.

Heuristic 1.5: Intermediate Line Section with Open Switch. If the line section is an intermediate line section and has an already open switch, then the line section is not a candidate to open.

Heuristic 1.6: Intermediate Line Section with Initially Closed Switch—Redundant Measure. If the line section is an intermediate line section and has a closed switch, then the line section is a candidate to open.

Network Radiality Rules for Closing an Initially Open Switch

Every switch has an upstream (supply) side and downstream (demand) side. When opening a switch, its upstream terminal switch will remain supplied with electricity. However, for the switch's downstream node, it is necessary to transfer the load to another substation. A breadth-first search is performed to determine what line sections are connected to the downstream node. The breadth-first search starts from the downstream node of the line section being cut and continues until a line section that meets all criteria has been found. If no viable line section is found during examination of the line sections connected to the downstream node of the switch being cut, then the hybrid fuzzy knowledge-based system will continue its breadth-first search by sequentially examining line sections connected to the end bus of each line section with no switch or a closed switch. If a switching combination is

identified that will preserve network radiality, then network layout tables are updated to ensure that network modifications are considered during subsequent analysis.

Heuristic 2.1: Line Section Previously Switched During an Interval in Distribution System Optimization. If the line section was previously switched in distribution system optimization during an interval, then the line section is not a candidate to close and this search path is disqualified.

Heuristic 2.2: Source Line Section. If the line section is a source line section, then the line section is not a candidate to close and this search path is disqualified.

Heuristic 2.3: Terminal Line Section. If the line section is a terminal line section, then the line section is not a candidate to close and this search path is disqualified.

Heuristic 2.4: Intermediate Line Section with No Switch. If the line section is an intermediate line section and does not have a switch, then the line section is not a candidate to close, but this search path is not completely disqualified.

Heuristic 2.5: Intermediate Line Section with Closed Switch. If the line section is an intermediate line section and has a closed switch, then the line section is not a candidate to close, but this search path is not completely disqualified.

Heuristic 2.6: Intermediate Line Section with Initially Open Switch—Redundant Measure. If the line section is an intermediate line section and has an initially open switch, then a potential switching combination has been identified.

Heuristic 2.7: Supply to the Initially Open Switch—Redundant Measure. If the start bus of the initially open switch has supply, then a potential switching combination has been identified.

Heuristic 2.8: Formation of an Isolated Loop. If the source trace from the start bus of the initially open switch does not cross the search path, then a successful switching combination has been identified.

Network Parameter Rules

Network parameter rules ensure that no network operational constraints are violated by a candidate switching combination.

Heuristic 3.1: Ensure Acceptable Fault Current Levels. If the switching operation includes existing switches, then the fault current level remains acceptable.

Heuristic 3.2: Line Section Capacity. If the line section loading is *excessive,* then the switching combination is *undesirable*. If there is an emergency condition and line section loading is *low, normal,* or *high,* then the switching combination has *high* desirability. If the temperature trend is *cold* and line section loading is *low* or *normal,* then the switching combination has *high* desirability. If the temperature trend is *cold* and line section loading is *high,* then the switching combination has *low* desirability. If the temperature trend is *normal* or *hot* and line section loading is *low,* then the switching combination has *high* desirability. If the temperature trend is *normal* or *hot* and line section loading is *normal,* then the switching combination has *moderate* desirability. If the temperature trend is *normal* or *hot* and line section loading is *high,* then the 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.

Heuristic 3.4: Transformer Aging Due to Temporary Transformer Overloading. If there will be a temporary transformer overload and transformer aging will be *low,* then the switching combination has *high* desirability. If there will be a temporary transformer overload and transformer aging will be *normal,* then the switching combination has *moderate* desirability. If there will be an emergency condition and temporary transformer overload and transformer aging will be *high,* then the switching combination has *moderate* desirability. If there will be a temporary transformer overload and transformer aging will be *excessive,* then the switching combination is *undesirable*.

Heuristic 3.5: Daily Transformer Aging. If transformer aging will be *low,* then the switching combination has *high* desirability. If transformer aging will be *normal,* then the switching combination has *moderate* desirability. If transformer aging will be *high,* then the switching combination has *low* desirability. If transformer aging will be *excessive,* then the 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 the voltage level is *unacceptable* or *emergency,* then invoke the voltage-update routine. If the voltage level is *overvoltage,* then invoke the voltage-update routine with CVR policy set. If the voltage-update routine is executed and the voltage level is *range B,* then the switching combination has *moderate* desirability. If the voltage-update routine is executed and voltage level is *range A,* then the switching combination has *high* desirability. If the voltage-update routine is executed and

there is an emergency condition and the voltage level is *emergency,* then the switching combination has *moderate* desirability. If the voltage-update routine is executed and there is a normal condition and the voltage level is *emergency* or *unacceptable,* then the switching combination is *undesirable.*

Heuristic 3.7: Adjustment of Reactive Power Compensation. If the load is transferred to the substation and the main feeder is equipped with switched capacitors, then switch in capacitors according to 2/3 rule (Sarfi and Solo 2002b). If the load is shed by the substation and the main feeder is equipped with switched capacitors, then switch out capacitors according to 2/3 rule (Sarfi and Solo 2002b).

Heuristic 3.8: Service Priority. If a priority customer is supplied by several service entrances, then the customer is to be supplied by two different utility substations.

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 heuristic 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. [1988]). If $\Delta v_{sub\ 1\text{-}a} > \Delta v_{sub\ 2\text{-}b}$, then the transfer of bus A to substation 2 has *moderate* desirability. If $\Delta v_{sub\ 1\text{-}a} > \Delta v_{sub\ 2\text{-}b}$, then the transfer of bus A to substation 2 is *undesirable* where bus A is connected to substation 1, bus B is connected to substation 2, $\Delta v_{sub\ 1\text{-}a}$ is the voltage drop from substation 1 to bus *A,* and $\Delta v_{sub\ 2\text{-}b}$ is the 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.[2] If the voltage level is *range A* or *overvoltage* and system status is not *emergency*, then invoke the voltage-update routine with CVR option.

Heuristic 4.3: Heuristic Indices. Sarfi, Salama, and Chikhani (1994b) defined two heuristic indices 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 the switching combination is *undesirable.* If $C_2 > 0.75$, then the switching combination has *moderate* desirability.

Heuristic 4.4: Overall System Loss Reduction. If the aggregated assessment of losses is *low, moderate,* or *high,* then losses are reduced with the degree of desirability of the aggregated loss assessment and the candidate switching combination is accepted. If the aggregated assessment of losses is *undesirable,* then losses are reduced with the degree of desirability of the aggregated loss assessment and the candidate switching combination is not accepted.

Heuristic 4.5: Conversion Criteria. If the aggregated assessment of losses is *moderate* or *high* and all network radiality and network parameter rules are satisfied, then losses are reduced with the degree of desirability of the aggregated loss assessment and the overall system-optimization procedure is accepted. If the aggregated assessment of losses is *unacceptable* or *low,* then losses are reduced with the degree of desirability of the aggregated loss assessment and the 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 that 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.

Fuzzy Inference Mechanism

Fuzzy variables possibly modified by linguistic hedges can be defuzzified using the center of gravity defuzzification formula to obtain a single crisp representative value. In equation 1 for center of gravity defuzzification, μ is the degree

of membership, x is the domain value, A is the membership function possibly modified by linguistic hedges, and x_0 is the single crisp representative value.

$$x_o = \frac{\int_x \mu_{\tilde{A}}(x) x dx}{\int_x \mu_{\tilde{A}}(x) dx}$$

In addition to being able to model imprecise knowledge, a key advantage of fuzzy logic is its inherent ability to resolve conflicts. An example is provided to highlight the benefits of the fuzzy inference process for conflict resolution when input stimuli lie in a gray area. Consider the following criteria: (1) recent temperature trend is *normal,* and (2) line section loading following load transfer is 0.675 pu.

As illustrated in figure 3, a line section loading of 0.675 pu is a member of two line section loading sets: *low* with a degree of membership of 0.25, and *normal* with a degree of membership of 0.5. The degree of membership of *normal* is slightly higher than that of *low*. The fuzzy rules described in heuristic 3.2 assign two possible solutions for the input stimuli described: *high* desirability with a degree of membership of 0.25 [MIN(0.25, 1)], and *moderate* desirability with a degree of membership of 0.5 [MIN (0.5, 1)]. There is greater membership in the moderate fuzzy set, so the final consequent is *moderate* desirability with a degree of membership of 0.5 [MAX (0.25, 0.5)].

Validation and Simulations

The intelligent optimization system was validated and simulated on a subsystem of an actual 4.4-kilovolt 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 and holidays, winter weekdays, and winter weekends and holidays. Residential, commercial, industrial, and mixed-load types were represented in the simulations. Simulations showed that the optimization of power distribution system operation 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.

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.

The development of this hybrid knowledge-based system employing knowledge-based and numerical methods to perform a multiobjective optimization of power distribution system operation is a giant leap forward in the research literature (Sarfi, Salama, and Chikhani 1994a and 1996a). Previously published approaches do not optimize for as many objectives, offer as many means of control, comply with as many network constraints, and combine knowledge-based and numerical methods. The definition of heuristic rules for network radiality, network parameters, and network performance is in itself a substantial contribution to power systems theory. This is illustrated by the description of complexity in utility knowledge acquisition and conceptualization. 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. The approach described will also improve system reliability.

Notes

1. See IEEE C57.92-1981. IEEE guide for loading mineral oil–immersed power transformers up to and including 100 MVA with 55°C or 65°C average winding rise.

2. See ANSI C84.1-1995. Electric Power Systems and Equipment—Voltage Ratings (60 Hertz).

References

Civanlar, S.; Grainger, J.; Yin, H.; and Lee, S. S. H. 1988. Distribution Feeder Reconfiguration for Loss Reduction. *IEEE Transactions on Power Delivery* 3(2): 1217–1223.

Clancy, W. 1985. Heuristic Algorithms. *Artificial Intelligence* 27(3): 289–350.

Gonen, T. 1985. *Electric Power Distribution System Engineering*. New York: McGraw-Hill.

Gupta, M. M.; Jin, L.; and Homma, N. 2003. Fuzzy Sets and Systems: An Overview. In *Static and Dynamic Neural Networks: From Fundamentals to Advanced Theory,* 636–644. New York: John Wiley & Sons.

Gupta, U. G. 1991. *Validating and Verifying Knowledge-Based Systems*. Los Alamitos, CA: IEEE Computer Society.

Millington, D. 1981. *Systems Analysis and Design for Computer Applications*. Chichester, UK: Ellis Horwood.

Orchard, B. 2004. *FuzzyCLIPS Version 6.10d User's Guide*. Integrated Reasoning Group, Institute for Information Technology. Ottawa, ON: National Research Council Canada.

Sarfi, R. J., and Solo, A. M. G. 2002a. Inclusion of Human Operator Interaction in Performance Optimization of Power Distribution Operations. *Electric Power Systems Research* (61)3: 179–184.

Sarfi, R. J., and Solo, A. M. G. 2002b. Network Radiality, Parameter, and Performance Heuristics in Optimization of Power Distribution System Operations. Part 1: Crisp Rule Base. *International Journal of Electrical Power & Energy Systems* 24(8): 673–682.

Sarfi, R. J., and Solo, A. M. G. 2002c. Network Radiality, Parameter, and Performance Heuristics in Optimization of Power Distribution System Operations. Part 2: Fuzzification of Rule Base. *International Journal of Electrical Power & Energy Systems* 24(8): 683–692.

Sarfi, R. J., and Solo, A. M. G. 2005a. The Application of Fuzzy Logic in a Hybrid Fuzzy Knowledge-Based System for Multiobjective Optimization of Power Distribution System Operations. In *Proceedings of the 2005 International Conference on Information and Knowledge Engineering,* 3–9. Las Vegas, NV: CSREA.

Sarfi, R. J., and Solo, A. M. G. 2005b. Integration of Numerical Methods in a Hybrid Fuzzy Knowledge-Based System for Multiobjective Optimization of Power Distribution System Operations. In *Proceedings of the Fourth IASTED International Conference on Computational Intelligence,* 42–49. Anaheim, CA: ACTA Press.

Sarfi, R. J., and Solo, A. M. G. 2006. A Hybrid Fuzzy Knowledge–Based System for Network Operational Constraints in Power Distribution System Reconfiguration. In *Proceedings of the 2006 IEEE International Conference on Fuzzy Systems*. Piscataway, NJ: IEEE Press.

Sarfi, R. J.; Salama, M. M. A.; and Chikhani, A. Y. 1994a. A Survey of the State of the Art in Distribution System Reconfiguration for System Loss Reduction. *Electric Power Systems Research* 31(1): 61–70.

Sarfi, R. J.; Salama, M. M. A.; and Chikhani, A. Y. 1994b. Distribution System Reconfiguration for Loss Reduction: A New Algorithm Based on a Set of Quantified Heuristic Rules. In *Proceedings of the 1994 Canadian Conference on Electrical and Computer Engineering,* 125–130. New York: Institute of Electrical and Electronics Engineers.

Sarfi, R. J.; Salama, M. M. A.; and Chikhani, A. Y. 1996a. Applications of Fuzzy Sets Theory in Power Systems Planning and Operation: A Critical Review to Assist in Implementation. *Electric Power Systems Research* 39(2): 89–101.

Sarfi, R. J.; Salama, M. M. A.; and Chikhani, A. Y. 1996b. Distribution System Reconfiguration for Loss Reduction: An Algorithm Based on Network Partitioning Theory. *IEEE Transactions on Power Systems*. 11(1): 504–510.

Sarfi, R. J.; Salama, M. M. A.; Vannelli, A.; and Chikhani, A. Y. 1993. Loss Reduction in Distribution Systems: A New Approach Using Partitioning Techniques. In *Proceedings of the 1993 IEEE Industry Applications Society Annual Meeting*, vol. 2, 1439–1444. New York: Institute of Electrical and Electronics Engineers.

Solo, A. M. G.; and Sarfi, R. J. 2005. A Knowledge-Based System for Network Radiality in a Power Distribution System. In *Proceedings of the 2005 International Conference on Artificial Intelligence*, vol. 2, 918–924. Las Vegas, NV: CSREA.

Robert Sarfi, a partner at Boreas Group LLC, provides business vision and technology solutions to electric and gas utilities around the world. Prior to Boreas Group, Sarfi occupied numerous leadership positions with consulting firms focused on providing technology consulting to electric and gas utilities. Sarfi has a bachelor's degree and Ph.D. in electrical engineering. He is a licensed professional engineer in the province of Ontario and a member of IEEE.

Ashu M. G. Solo is an electrical and computer engineer, mathematician, writer, and entrepreneur. His primary research interests are in mathematics, intelligent systems, public policy, and the application of intelligent systems in control systems, computer architecture, power systems, optimization, pattern recognition, decision making, and public policy. After working in industry and universities, Solo now works for his own company Maverick Technologies America Inc. Solo previously served honorably as an infantry officer and platoon commander understudy in the Canadian Army Reserve. He can be reached at amgsolo@mavericktechnologies.us.