British Journal of Applied Science & Technology
12(6): 1-15, 2016, Article no.BJAST.21968
ISSN: 2231-0843, NLM ID: 101664541

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Design and Planning Support Tool for Interconnected Micro Energy Grids

Hossam A. Gabbar[1*]

[1]Faculty of Energy Systems and Nuclear Science and Faculty of Engineering and Applied Science, University of Ontario Institute of Technology (UOIT), ON, Canada.

Author's contribution

The sole author designed, analyzed and interpreted and prepared the manuscript.

Article Information

DOI: 10.9734/BJAST/2016/21968
Editor(s):
(1) Rui Xiao, School of Energy and Environment, Southeast University, China.
Reviewers:
(1) Anonymous, St. John's University, Taiwan.
(2) Hermes José Loschi, University the Campinas (UNICAMP), Brazil.
Complete Peer review History: http://sciencedomain.org/review-history/12080

Original Research Article

Received 11th September 2015
Accepted 29th September 2015
Published 3rd November 2015

ABSTRACT

The need for more flexible energy systems, changing regulatory and economic scenarios, energy savings and environmental impact are providing impetus to the development of micro energy grids, which are predicted to play an increasing role in future power systems. The purpose of this study is to design an efficient integrated simulation tool to estimate life cycle costs of micro energy grid (MEG) for practical implementation. The proposed tool comprises of engineering design modeling of power, thermal and fuel systems within a selected region or community to maximize the use of local resources and minimize the cost of the implementation of micro energy grid. The criteria of choosing the optimal MEG configuration is based on the life cycle costing of available local resources components and estimation of MEG overall cost. The proposal also includes the development of intelligent algorithms for the optimization of life cycle costing of MEG with the selection of best design and configuration alternatives of micro energy grids with power/thermal/fuel loads will be introduced.

Keywords: Smart energy grids; distributed modeling and simulation; distributed control; safety and protection; resilient smart energy grids.

**Corresponding author: E-mail: Hossam.gabbar@uoit.ca;*

1. INTRODUCTION

In recent years there has been a global movement in the direction of adoption and deployment of distributed and renewable resources. Renewable energy (RE) sources differ from conventional sources in that, generally they cannot be scheduled, they are much smaller than conventional power stations and are often connected to the electricity distribution system rather than the transmission system. The integration of such time variable distributed or embedded sources into electricity network requires special consideration. Due to ever-increasing demand for high–quality and reliable electric power, the concept of distributed energy resources (DER) has attracted widespread attention in recent years [1]. Distributed energy resources consist of relatively small-scale generation and energy storage devices that are interfaced low or medium voltage distribution networks and can offset the local power consumption, or even export power to the upstream network if their generation surpasses the local consumption. An upcoming philosophy of operation which is expected to enhance the utilization of distributed energy resources is known as the microgrid concept [2,3]. Microgrids should widely utilize renewable energy resources such as wind, sunlight, and hydrogen, to play a significant role in the electric power systems of the future, for cleaner air, reduced transmission and distribution costs, and enablement of energy efficiency enhancement initiatives. In addition, using energy storage devices such as batteries, energy capacitors, flywheels, controllable loads, etc. along with the DG units make the MGs operate in a more flexible and economic manner [4,5]. From a customer's point of view, microgrids similar to traditional LV distribution networks not only provide their thermal and electricity needs, but in addition, enhance local reliability, reduce emissions, improve power quality by supporting voltage and reducing voltage dips, and lead to lower costs of energy supply [6]. Several researches have been performed to optimize the operation, load dispatch and management of energy storage system (ESS) of the MGs. Particle swarm optimization method accordingly is employed in Ref. [7] to minimize the cost of MGs with controllable loads and battery storage. This is done by selling the stored energy at high prices and shave peak loads of the larger system. Linear programming algorithm is used in Ref. [8] to optimize MG operation cost and battery charge states. Maximizing benefits owing to the energy pricing differences between on-peak and off-peak periods are obtained by electrical and thermal storage charge scheduling in Ref. [9,10].

The important drawback of above study is that it does not consider all uncertainties of the problem. Although employing Renewable Energy Sources (RES) obviate environmental concerns and fossil fuel consumption, they introduce uncertain and fluctuated power because of the stochastic wind and solar variation [11-13]. In addition, regarding to open access power market and diverse commercial, residential and industrial consumer types, daily load demand also has a random nature [14]. Moreover, in an open access power market, the degree of uncertainty of the load forecast error and market price can be even more perceptible. Engineers require computational methods which could provide solutions less sensitive to the environmental effects, so the techniques should be used which take the uncertainty to account to control and minimize the risk associated with design and operation [15]. In order to consider uncertainty in optimal energy management planning of MGs effectively, the optimization problem should be solved for a suitable range of each uncertain input variable instead of just one estimated point. Using deterministic optimization problem, a large computational burden is required to consider every possible and probable combination of uncertain input variables. Hence, from the system planning point of view, it turns out to be convenient to approach the problem of energy management planning of the MGs as a probabilistic problem. This leads to the problem known as energy management planning under uncertainty, where the output variable of a microgrid objective function obtained as random variable, and thus, it becomes easy to identify the possible ranges of the total operating cost.

Microgrid can be viewed as the small scale of AC/DC power grid that meets local electricity demand [16]. Micro energy grids (MEGs) are integrated small scale energy grid that includes electricity, thermal, and gas networks that integrate transportation and water networks to meet local demand including storage and conversion technologies. Smart energy grids (SEG) will include interconnected MEGs [17].

There are several techniques to deal with problems under uncertainty. The three main approaches are analytical, simulation (Monte Carlo simulated) and approximate methods [18]. The vast majority of techniques have been analytically based and simulation techniques have taken a minor role in specialized applications. All the proposed solutions for energy management of microgrids dealt with the microgrid as a micro power grid comprises electric supplies and loads and not as a micro energy grid in spite of existence of thermal and fuel supplies and loads [19].

This paper describes the development of support tool for the design and operation of micro energy grids with the main objective of improving energy efficiency with conservation strategies in communities, commercial and residential buildings, industrial facilities, and transportation. This will support the deployment of high performance energy supply grids with more penetration of natural gas applications such as boilers, natural gas vehicle, and natural gas fuel cells. In addition, it will enable the penetration of high performance solar systems and their applications in water and air heating, and co-generation. The proposed project will include sensor network infrastructure to monitor and control micro energy grids and loads in efficient ways.

2. SMART ENERGY GRID (SEG) SUPERSTRUCTURE

2.1 Energy Supply and Production Chain

In order to optimize the energy supply locally in each region and as interconnected regions, process object-oriented modeling methodology (POOM) was introduced and used to model energy generation, supply topology, and link to usage nodes. For better representation of energy grid networks, Energy Semantic Networks (ESN) is used to represent energy grids physical model as well as associated constraints and business rules.

Fig. 1 shows the proposed modeling of regional energy supply chain, which was originally explained in [1]. The corresponding energy model is developed to analyze energy production from thermal, electricity, and fuel, which are mapped to energy usage. Table 1 shows the details of the model.

2.2 Modeling Energy Generation / Conversion

The proposed model is implemented in computer-aided design tool in Visio and the corresponding ESN knowledgebase is implemented in Microsoft database based on POOM and in view of ISA S95. Each building block of the proposed energy network is modeled using POOM where process variables (inputs, internal, and output) are represented in systematic way so that key performance indicators (KPIs) can be represented in each detailed building block, such as solar system, wind mill, thermal storage unit, and fuel cell unit and battery banks, as shown in Fig. 2.

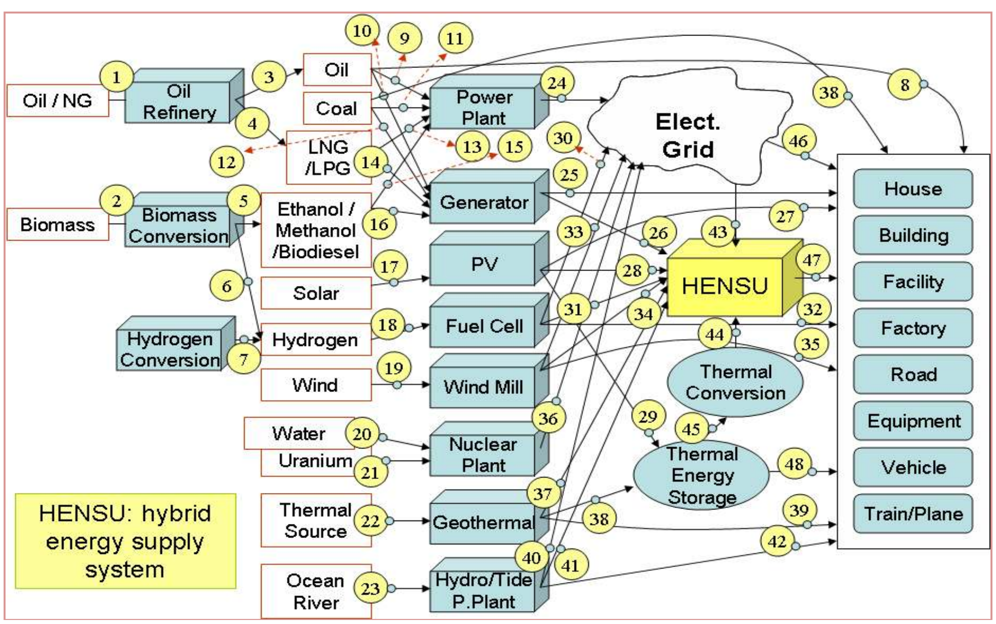

Fig. 1. Energy production and supply chain model

Table 1. Energy model details

Model element	Definition	Links
Oil and natural gas	Oil and natural gas supply to oil refinery production process	It supplies oil and coal
Biomass	Biomass supply from different domestic sources into biomass conversion to produce ethanol, methanol, biodiesel	It supplies biofuel to power plants, and generators
Hydrogen	Hydrogen generation from water, or other sources	Supplies hydrogen to fuel cell, also can supply to transportation (vehicles, rail, etc.)
Water / Uranium	Supplies to nuclear facilities, to produce power and thermal	It supplies power to the energy grid as well as HENSU, Hybrid Energy Supply Unit in different levels
Thermal	It supplies thermal energy with technologies such as geothermal	It supplies thermal energy to thermal loads and thermal storage
Ocean / Rivers	It supplies power via hydro power plants and other tide technologies	It supplies power to energy grid and to HENSU
PV	It provides electricity and thermal from solar	It supplies electricity and thermal to energy grid, HENSU, and other thermal loads
All	It supplies energy to different loads	Facilities, houses, transportation, infrastructures, equipment, etc.

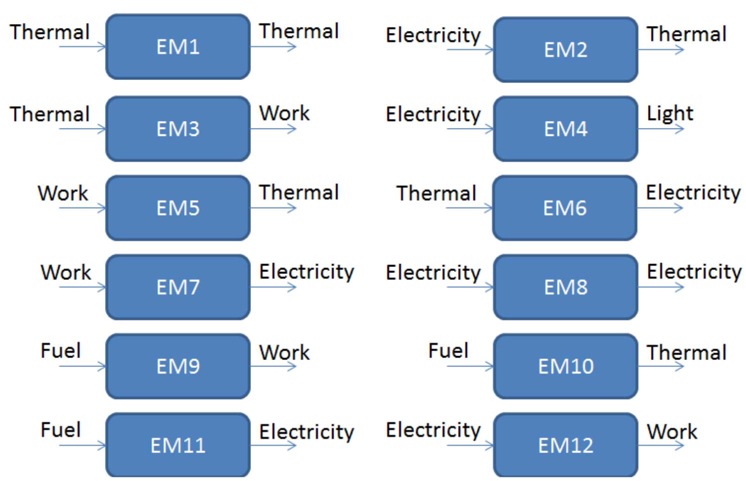

Fig. 2. Modeling of energy node within ESN using POOM

2.3 Energy Semantic Networks (ESN)

Energy Semantic Network (ESN) is a dynamic and adaptive structure to model and simulate energy supply and production chains [1]. ESN provides means to integrate generation (G), storage (S), and loads (L). ESN is used also to integrate electricity (E), gas (G), and thermal (T) grids. ESN is also used to interconnect Micro Energy Grids (MEGs), with transfer lines (T) between MEGs. Fig. 3 shows the proposed ESN to model Transmission Lines (TL) / Distribution Lines (DL) of electricity networks (EN), gas networks (GN), thermal networks (TN), water networks (WN), and transportation networks (RN). ESN includes the integration of TL/DL with MEGs via electricity feeder lines (EF) with percentage REF%, gas feeder lines (GF) with percentage RGF%, thermal feeder lines (TF) with percentage RTF%, water feeder lines (WF) with percentage RWF%, and transportation feeder lines (RF) with percentage RRF%. ESN includes nodes of energy generation: electricity generation (EG) with percentage REG%, gas generation (GG) with percentage RGG%, and thermal generation (TG) with percentage RTG%; energy storage: Electricity storage (ES) with percentage RES%, gas storage (GS) with percentage RGS%, and thermal storage (TS) with percentage RTS%; and energy loads:

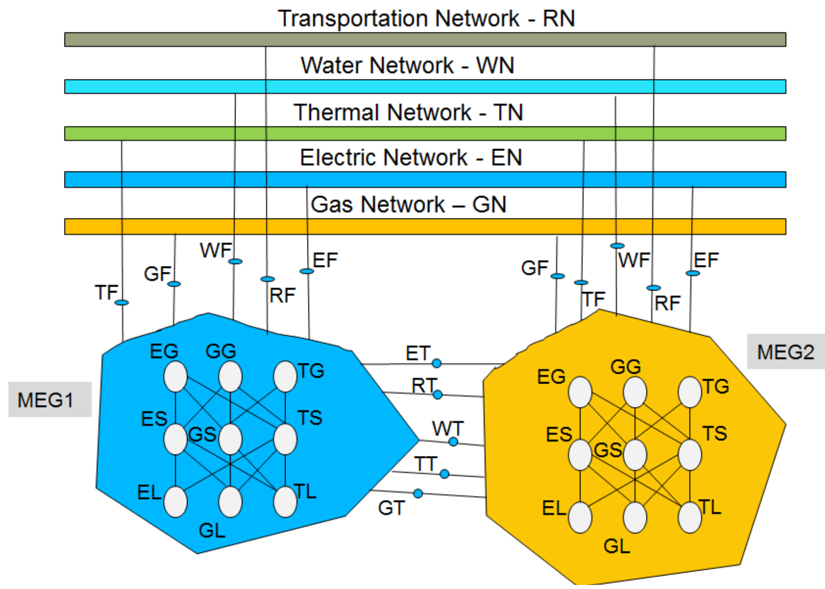

Fig. 3. Energy Semantic Network (ESN) with interconnected micro energy grids within SEG

electricity loads (EL) with percentage REL%, gas loads (GL) with percentage RGL%, and thermal loads (TL) with percentage RTL%. The interconnection between MEGs includes: electricity transfer lines (ET) with percentage RET%, thermal transfer lines (TT) with percentage RTT%, gas transfer lines (GT) with percentage RGT%, water transfer lines (WT) with percentage RWT%, and transportation transfer lines (RT) with percentage RRT%. ESN static structures are synthesized and dynamically tuned with computational intelligence techniques using real time data and simulation.

3. MEG ENGINEERING DESIGN

Fig. 4 shows an integrated engineering design of MEG, which shows electricity, thermal, and gas networks with supply, generation, storage, and loads components.

3.1 MEG Power Model

In this power model, a simulation library of all energy resources such as wind, PV, micro gas turbine and fuel cells is introduced with taking into account the intermittent nature of these resources, as shown in Fig. 5. The modeling of all variable profiles electric loads based on constant power model will be achieved.

3.2 MEG Thermal Model

This module is based on building the energy Symantec network (ESN) of MEG, for options of thermal network modeling. The ESN model takes into account all aspects of the thermal network modeling that includes a variety of 73 different working fluids available to be used inclusion of the thermo-fluidic components such as boiler, pumps, thermal tanks, heat exchangers, condensers, and expansion valves is essential but is not limited to allow for modeling the heat pumps and air conditioning units, as shown in Fig. 6.

3.3 MEG Gas Model

The third step required for the research project is to build a general diagram which depicts the fuel sources and loads use within MEG. The natural gas and hydrogen is the most clean fuel sources in the new communities. Fig. 7 shows the most generic and high level representation for the use of fuel within MEG where blue pipelines indicate the electrical uses for MEG and red indicates the thermal uses within MEG.

3.4 Fuel Cell Modeling

In fuel cell model, input variables: Fuel flow rate (l/min), Air flow rate (l/min), Pressure of fuel (atm), Pressure of Air (atm), percentage of hydrogen in fuel (x), percentage of oxygen in the oxidant (y). These input variables affect the open circuit voltage (E_{oc}), the exchange current (i_0) and the Tafel slope (A).

$$E_{oc} = K_c E_n$$
$$i_0 = \frac{zFk\,(P_{H_2} + P_{O_2})}{Rh} e^{\frac{-\Delta G}{RT}} \quad (1)$$
$$A = \frac{RT}{z\alpha F},$$

Where,

R = 8.3145 J/(mol K)
F = 96485 A s/mol
z = Number of moving electrons
E_n = Nernst voltage, which is the thermodynamics voltage of the cells and depends on the temperatures and partial pressures of reactants and products inside the stack (V)
α = Charge transfer coefficient, which depends on the type of electrodes & catalysts used
P_{H2} = Partial pressure of hydrogen inside the stack (atm)
P_{O2} = Partial pressure of oxygen inside the stack (atm)
k = Boltzmann's constant = 1.38 × 10^{-23} J/K
h = Planck's constant = 6.626 × 10^{-34} J s
ΔG = Size of activation barrier which depends on the type of electrode & catalyst used
T = Temperature of operation (K)
K_c = Voltage constant at nominal condition of operation

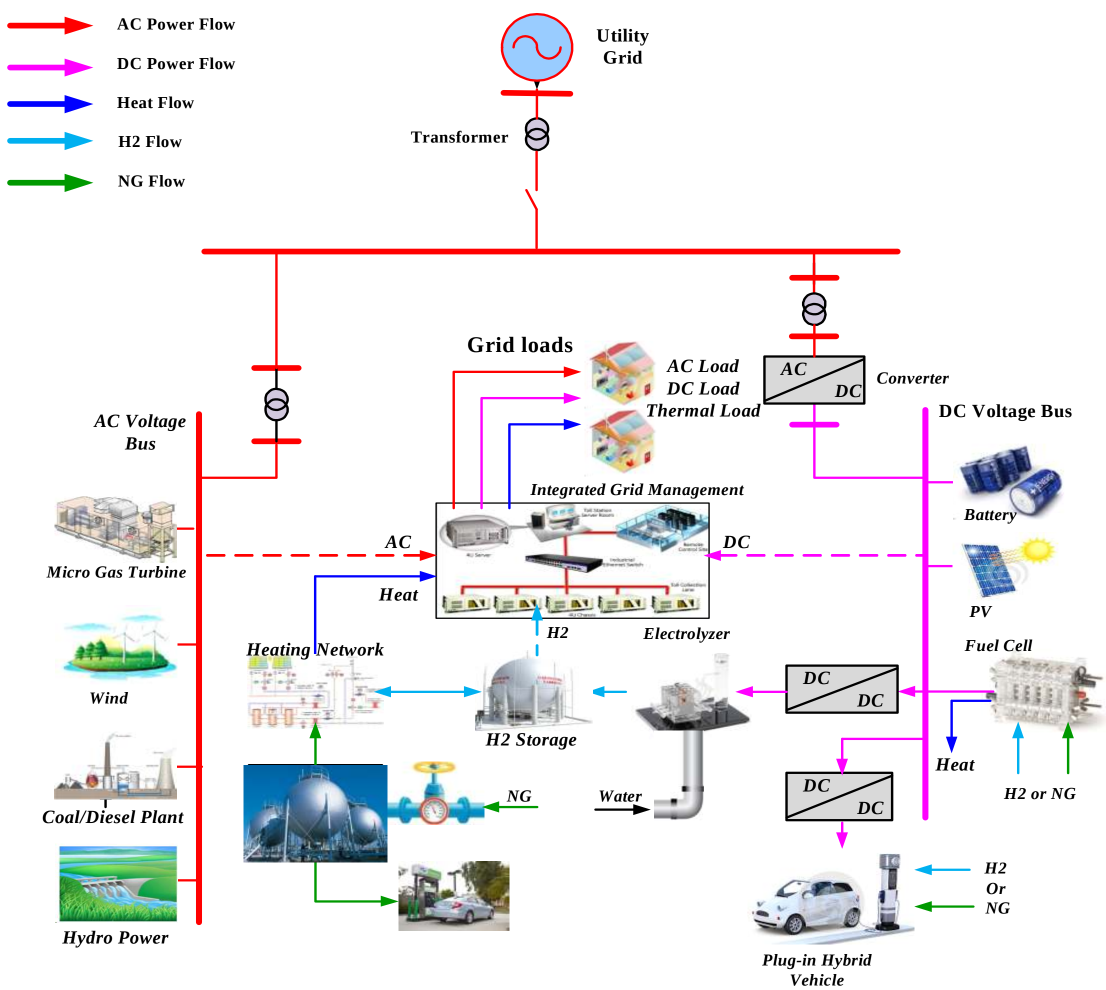

Fig. 4. MEG integrated design

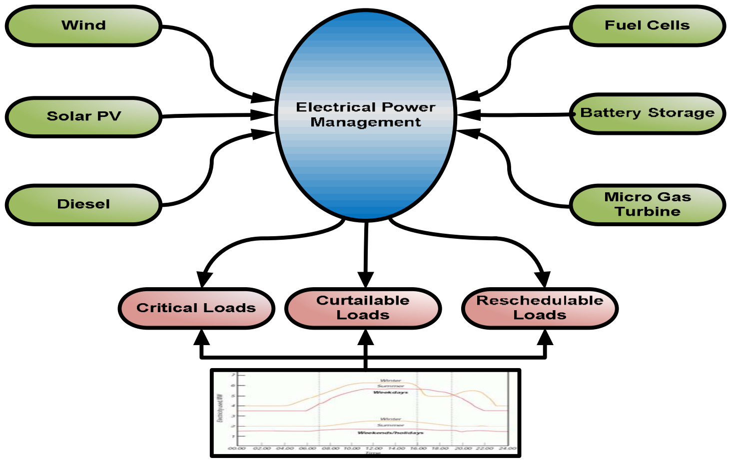

Fig. 5. MEG power configurations

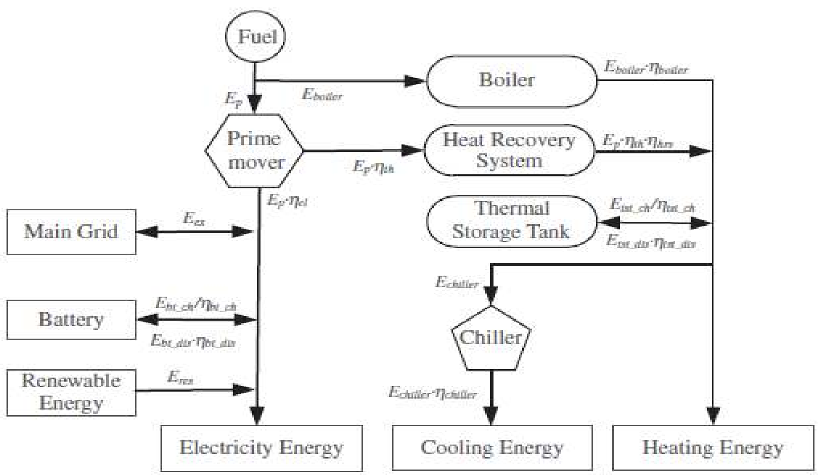

Fig. 6. MEG thermal model configurations

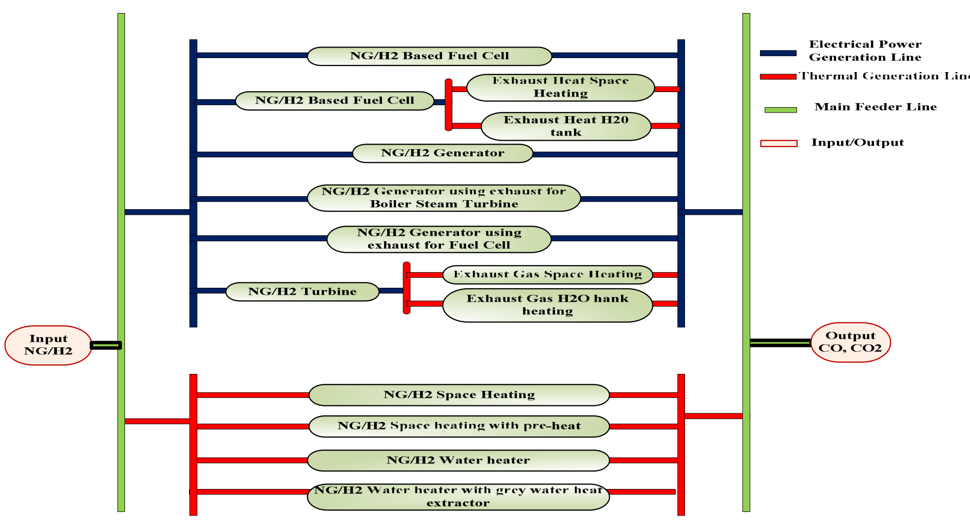

Fig. 7. MEG gas model configurations

4. KPI MODELING OF SEG / MEG

The proposed MEG simulation framework starts with MEG model library development for all potential distributed energy resources (DERs) that can be utilized within MEG. This is followed by collecting demand requirements of thermal, fuel, power within MEG. Based on the demand requirements, possible MEG design and configuration alternatives will be synthesized for thermal, fuel, and power systems. For each design and configuration scenario, KPIs will be estimated for each component, and MEG level, and will be evaluated and optimized using MEG simulation engine that is developed in Matlab.

4.1 Economic KPI Modeling

Economical KPIs include different operational and maintenance costs of a building like flexibility, adaptability, affordability, and manageability. Under the economic KPIs, the total operation and maintenance cost of energy resources in a building can be calculated as

$$C_{ann\_op} = \sum_{h=1}^{8760}\sum_{i=1}^{n}[k_{f_i} \times P_i(h) + k_{m_i} \times P_i(h)]. \qquad (2)$$

Where, C_{ann_op} is annual operation cost of the energy resources in the building, k_{f_i} is fuel cost of i^{th} unit ($/kWh), k_{m_i} is the average periodic and reactive maintenance cost of i^{th} unit ($/kWh), and $P_i(h)$ is the power consumed by the i^{th} unit.

The locations of manufacture and deployment of renewable energy technologies affect the life cycle energy requirements, greenhouse gas emissions, and economic costs.

- To conduct life cycle assessments (LCAs) of the following energy technologies:
  - Solar PV
  - Small wind
  - Fuel cells
  - Energy storages
  - Extension of the electricity grid.
- To review published LCAs of the above technologies that were conducted under standard test conditions (STC).
- To compare the LCAs for the above technologies under STC and local conditions and determine which has the lowest life cycle impact.
- To optimize LCC of MEG design and operation alternatives and provide the most economic MEG configuration to support stakeholders' decision.

Life cycle assessments for renewable energy technologies are widespread and well established. Many of these LCA studies have been conducted using standard test conditions (STC). On one hand, STC provides a standard against which different technologies and innovations can be compared. On the other hand, STC may not reflect actual performance in the field, especially when field conditions differ substantially from STC. The proposed work would be the first LCA of solar PV and wind turbine systems.

The ISO 14040 standard provides a general framework for conducting LCAs, but it does not specify a particular procedure as shown in Fig. 6. The ISO framework identifies four phases of an LCA. In the first step, the LCA goals, scope, and system boundaries are defined. The second phase is inventory analysis in which material and energy inputs and outputs are analyzed. This is the main data collection phase. The third phase, impact assessment, describes the environmental significance of the inventory analysis. The life cycle cost assessment is conducted on different micro energy gird configuration scenarios to provide decision support to the deployment alternatives of renewable energy within micro energy grids.

Setup Cost: The following is the current estimate of Micro Grid power consumption (in Ontario):

20 MW for 15 hours/day = 300 MWh
10 MW for 9 hours/day = 90 MWh
Average power consumption/day = 390 MWh

The consumption estimate above is based on the idea that most of UOIT's power needs are between 7AM – 10PM when the university is open and most of the students are on campus attending classes. This translates to 15 hours of maximum power of 20MW required to meet the demands. As for the remaining 9 hours, the demand can be estimated to be 10MW.

Based on the above estimate for UOIT's power consumption, and the current wholesale average price of 2.96 cents/kWh as outlined by IESO; the current cost per day for hydro is approximately $11,544. The calculations are shown below:

Cost of hydro/day = (Average power consumption/day) X (current wholesale average price)

= (390 MWh) X (2.96cents/kWh)
= (390,000kWh) X (2.96cents/kWh)
= $11,544/day (3)

Based on the above estimate, the yearly cost can be found to be:

(Cost of hydro/day) X (365 days/year) =
$11,544/day X 365 days/year = $4,213,560 (4)

Wind Cost: The costs associated with setting up solar power are approximately $1 for every needed watt. As for wind, the costs are $5/watt of power required. Seeing as the cost of implementing solar energy is considerably less than wind, it would be cost effective to fulfill the power requirements of UOIT in the following manner: 60% of power fulfilled through solar energy and the rest 40% through wind generation. Below is the cost breakdown for the implementation of this form of renewable generation.

Solar: $1/watt X (60% of 20MW) = $12 million
Wind: $5/watt X (40% of 20MW) = $40 million

Consequently, the total cost for implementing solar and wind energy systems for UOIT would be $12 million + $40 million = $52 million.

4.2 KPI Modeling of Energy Storage

One of the critical components of our micro grid design is power storage and one type of storage device is a lithium ion battery. Modeling these components is part of our revised requirements. These models will allow for better design decisions, as well as play a role in the simulations. The equation models [5,7] of the chosen battery model are derived as shown below. Similar models are developed for different energy generation and storage of thermal, gas, and electricity and linked with performance indicators.

$$V_{BATTERY} = V_{OC} - I_{BATTERY} \times Z_{EQ} + (\Delta E) \quad (5)$$

$$\%\,Storage\ Loss = (1.544)(107)(t)e^{(40498é(8.3143T))} \quad (6)$$

4.3 Environmental and Reliability KPIs

Environmental KPIs include, water conservation, greenhouse gas (GHG) emission, materials, durability, waste, safety, and environmental risk factors. The reliability KPIs include operational reliability of building energy resources including condition based maintenance indicators, remaining useful life predictors, and equipment power factors. Reliability gives an indication of how a system performs without any maintenance. The reliability indicators include maintainability, operational availability, functional availability, and decision capability.

4.4 Quality KPI Modeling

Quality KPIs include CO_2, humidity, and individual dissatisfaction index. The CO_2 concentration for an energy zone can be calculated as:

$$\rho_{air} V_z C_{CO_2} \frac{dC_z^t}{dt} = \sum_{i=1}^{N_{sl}} kg_{mass_{sl}} \times 10^6 + \ldots$$
$$\sum_{i=1}^{N_{zones}} \dot{m}_i \left(C_{zi} - C_z^t \right) + \dot{m}_{\inf} \left(C_\infty - C_z^t \right) + \dot{m}_{sys} \left(C_{\sup} - C_z^t \right). \quad (7)$$

Where, $\sum_{i=1}^{N_{sl}} kg_{mass_{sl}}$ is sum of scheduled internal carbon dioxide (CO_2) loads, the term 10^6 is used to make the units of CO_2 as parts per million (ppm), $\sum_{i=1}^{N_{zones}} \dot{m}_i \left(C_{zi} - C_z^t \right)$ is CO_2 transfer because of inter-zone air mixing and can be expressed as ppm-kg/s, C_{zi} is CO_2 concentration in zone air as ppm, $\dot{m}_{\inf} \left(C_\infty - C_z^t \right)$ is CO_2 transfer because of infiltration and ventilation and is expressed as ppm-kg/s, C_∞ is CO_2 concentration outdoor air as ppm, $\dot{m}_{sys} \left(C_{\sup} - C_z^t \right)$ is CO_2 transfer because of system supply as ppm-kg/s, $C_{\sup}$ is CO_2 concentration in system supply air as ppm, $\dot{m}_{sys}$ is air system supply mass flow rate as kg/s, $\rho_{air} V_z \frac{dC_z^t}{dt}$ is CO_2 storage term in zone air as kg/s, C_z^t is zone air CO_2 concentration at current time stamp as ppm, ρ_{air} is zone air density as kg/m^3, V_z is zone volume as m^3, and C_{CO_2} is CO_2

capacity multiplier. The humidity factor for an energy zone can be calculated as

$$\rho_{air} V_z C_W \frac{dW_z^t}{dt} = \sum_{i=1}^{N_{sl}} kg_{mass_{sl}} + \dots$$
$$\sum_{i=1}^{N_{surfaces}} A_i h_{mi} \rho_{air_z} \left(W_{surfs_i} - W_z^t \right) + \sum_{i=1}^{N_{zones}} \dot{m}_i \left(W_{zi} - W_z^t \right) + \dots \quad (8)$$
$$+ \dot{m}_{\inf} \left(W_\infty - W_z^t \right) + \dot{m}_{sys} \left(W_{\sup} - W_z^t \right).$$

Where, $\sum_{i=1}^{N_{sl}} kg_{mass_{sl}}$ is sum of scheduled internal moister loads, $\sum_{i=1}^{N_{surfaces}} A_i h_{mi} \rho_{air_z} \left(W_{surfs_i} - W_z^t \right)$ is convection to zone surfaces, $\sum_{i=1}^{N_{zones}} \dot{m}_i \left(W_{zi} - W_z^t \right)$ is moisture transfer due to multi-zone airflow and can be expressed in kgWater/s, W_{zi} is humidity concentration in zone air in kgWater/kgDryAir, $\dot{m}_{\inf} \left(W_\infty - W_z^t \right)$ is moisture transfer because of infiltration in kgWater/s, W_∞ is moisture concentration of outdoor air in kgWater/kgGryAir, $\dot{m}_{sys} \left(W_{\sup} - W_z^t \right)$ is moisture transfer because of system supply, $\dot{m}_{sys}$ is air system supply mass flow rate in kg/s, $W_{\sup}$ is moisture concentration in system supply air in kgWater/kgDryAir. W_z^t is zone air moisture concentration at current time stamp in kgWater/kgDryAir. The degree of individual dissatisfaction index (DID) can be calculated as:

$$DID = \frac{1 + \tanh(2|vote| - 3)}{2}. \quad (9)$$

Where, $vote$ is

$$vote = \begin{cases} +3 & T > T_o + 2\Delta T \\ -3 & T < T_o - 2\Delta T \\ 1.5 \dfrac{T - T_o}{\Delta T} & Otherwise \end{cases}. \quad (10)$$

Where, T_o is set point or desired temperature in ^{o}C, T is current temperature in the room and ΔT is individual's temperature tolerance.

5. MODELING AND SIMULATION

One important feature in the proposal is to provide synchronization between real time grid data and simulation engine. This is important in two folds: (a) start simulation scenarios with initial conditions using real time data from the grid; and (b) fine tune simulation models using real time data. This is achieved by building intelligent interface program that captures real time data from the grid and map to the state variables in the simulation engine, which will tune simulation models using Genetic Programming with limited iteration to reduce the error between simulation results and real time. On the other side, it is possible to predict future status of the grid loads / demands by using smaller time step of the simulation starting from current condition of the grid as the initial condition. This will provide accurate estimation of loads / demands and identify / plan best ways of recovery operation. And in order to support decision making, intelligent algorithms will be developed to convert simulation data into qualitative models with symbolic representation that will support decision making. In terms of the simulation engine, and for interoperability purposes to support the wider range of commercialization, the simulation interface will be developed to interface with major simulation engines available in the market such as DIgSILENT PowerFactory, CYMDIST, ETAP, Paladin Design, EMTP / PSCAD, SimPowerSystems (SPS), and PSS1. The idea is to allow parameter passing between the simulation engine and the simulation interface program in two ways so that simulation results are captured, each time step, and update the database for tuning simulation models using the specified data analysis techniques.

5.1 SEG Infrastructure Modeling Framework

The proposed modeling and simulation environment will allow hierarchical and network levels of abstraction and specifications of Smart Energy Grid (SEG) components, which includes electricity grid, as connected to other networks like thermal and gas networks, as shown below.

Each component will be linked with knowledgebase for different model components: Business process, regulations, power, energy, asset integrity, physical topology, and geographical / environmental information.

Model libraries will be developed one with graphical symbol or icon, which represents the class level knowledge, so that user will be able to drag-and-drop in the drawing area and form or instantiate the corresponding objects. This will allow utilities to build the detailed grid model and dynamically tune with different design and operational alternatives. The modeling user interface is developed independent from any simulation engine with standard Microsoft library as shown in the figure below, as per the following tables. Fig. 8 shows typical infrastructure of smart energy grids where distributed generation and storage, and information technology infrastructure to integrate PMUs (Phasor Measurement Units), which are implemented in regional power grids.

Table 2. Transmission line infrastructures

#	Type of transmission line/Grid/Power sources	Code
1	High Voltage Direct Current line (HVDC)	TLD
2	High Voltage Alternating Current line (HVAC)	TLA
3	Low Voltage Distribution line	DL
4	Distribution grid/Substation	DG
5	Micro-grid	MG
6	Micro-grid Lines	ML
7	Power Plant such as Nuclear, Hydro, Coal etc.	PP
8	Transformer	T
9	Renewable sources such as Solar PV, wind farms etc.	RE
10	Energy storage	ES
11	Fuelling / Charging unit (Gas / PHEV)	CU

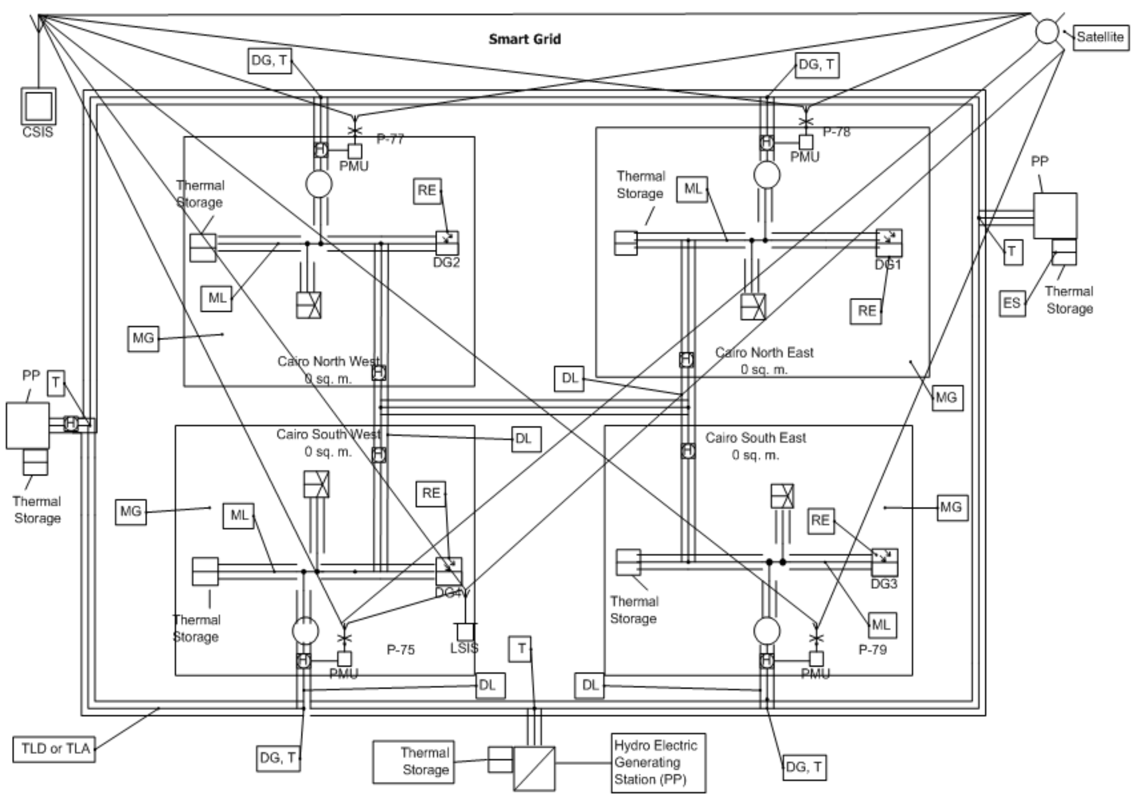

Fig. 8. Smart energy grid infrastructure editor

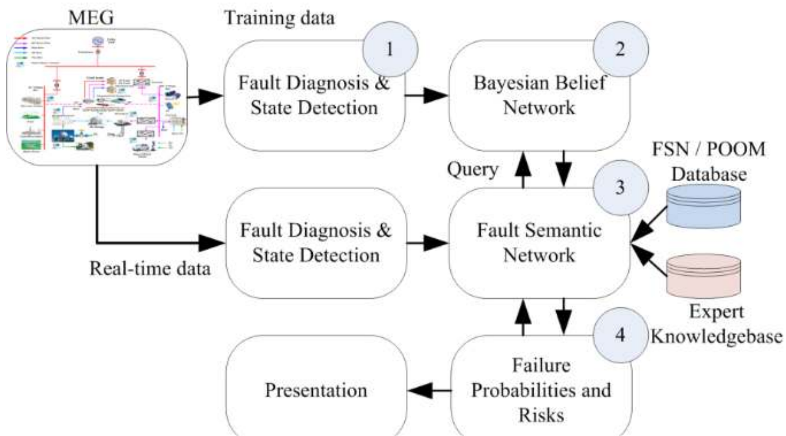

Fig. 9. Process to construct Fault Semantic Network (FSN)

Table 3. Power grid infrastructures

Code	Line type	Specs	From	To
TLD	High Voltage Direct Current line (HVDC)	800kV DC Voltage	Power plants far away from demand	Primary substation
TLA	High Voltage Alternating Current line (HVAC)	500kV AC Voltage	Power plants	Primary substation
DLM	Medium Voltage Distribution line	19.93kV, 34.5kV AC Voltage	Primary substation	Secondary substation
DLL	Low voltage distribution line	4.16kV, 2.4kV, 120V, 240V AC Voltage	Secondary substation	Customers such as industries, residential houses, etc.
ML	Micro-grid line	AC/DC	Micro-Grid	Low voltage distribution line

6. SAFETY / PROTECTION OF SMART ENERGY GRIDS

The proposed modeling and simulation will support real time safety verification based on advanced safety design approach. The concept of independent protection layers, or IPL, will be utilized to evaluate different risk scenarios and map to set of IPLs based on risk level, propagation time, and cost involved. This module will enable the development of safety design and hierarchical risk index based on reliability of grid components, loads, historical maintenance involved, and future operational plans / forecasting, as shown in the figure below. This will allow the dynamic tuning of risk index as linked to different components and displayed in the user interface in real time to enable operators and users to understand risks involved with different energy supply scenarios and to take suitable recovery actions.

6.1 Fault Semantic Network (FSN)

The concept of semantic network was first proposed as a network structure that represents relations between concepts. The concept of semantic network was further developed where semantic network was developed in a tree structure (directed or undirected graph) consisting of nodes and arcs. The nodes represent concepts and the connections show relations between nodes. Fault semantic network (FSN) originally realized as a mean of representing fault knowledge based on relationships among fault objects as mapped to physical systems. In FSN, the nodes correspond to different faults/causes/consequences and the links between them describe the dependencies. Initially, FSN is constructed based on ontology structure of fault models on the basis of process object oriented methodology (POOM) where failure mode (FM) is described using symptoms, enablers, variables, causes, consequences, and repair actions. Quantitative (probabilistic) or qualitative rules are associated with each transition of the causation model within FSN.

6.2 Framework for Safety and Protection of Smart Energy Grids

The proposed safety and protection framework is based on identifying all possible fault propagation scenarios using FSN, and estimating dynamic risks associated with each fault propagation scenario while mapping independent protection layers within each fault propagation scenario. FSN will be dynamically tuned with real time data using computational intelligence algorithms, as shown in Fig. 10.

7. MODELING AND SIMULATION INTERCONNECTED MEG

This paper introduces a novel integrated simulation tool to support the design, planning, and operation of SEG/MEG based on the optimization of power, thermal and fuel supplies and loads with the considerations of intermittent natural of DERs and the profiles of the different types of loads (electric, thermal and fuel loads) using life cycle costing of the DERs. Micro Energy Grid (MEG) as shown in Fig. 10 is an emerging concept in intellectual networks that integrates different energy resources like electricity, heat, hydrogen, and natural gas. MEG needs to be more reliable, secure, economic, eco-friendly, and safer. To introduce an integrated simulation tool for efficient cost and optimization of MEG, the following steps should be applied.

The different MEG energy models are integrated in a single simulation tool to decide the best MEG configuration based the combinations of the different models supplies and load with taking into account the intermittent natural of DERs and variable demand profiles. The life cycle cost is used to assess the best MEG configuration.

For practical implementation of SEG/MEG simulation and planning tool, a system architecture is proposed, as shown in Fig. 11. It shows knowledgebase components and system components that links business models with inference engines, user interface, outage management, transportation electrification, and real time data analysis. Distributed simulation engine is proposed to integrate power, thermal, gas, and transportation network simulation.

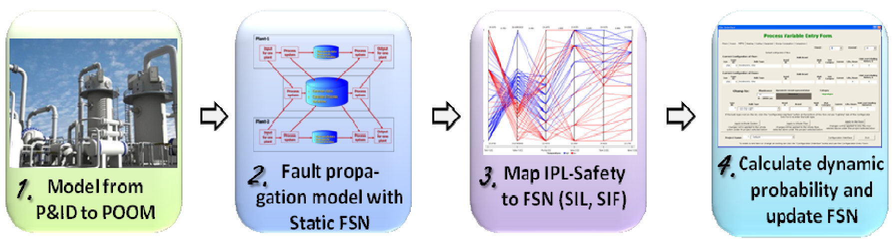

Fig. 10. Framework for FSN-based safety and protection design of smart energy grids

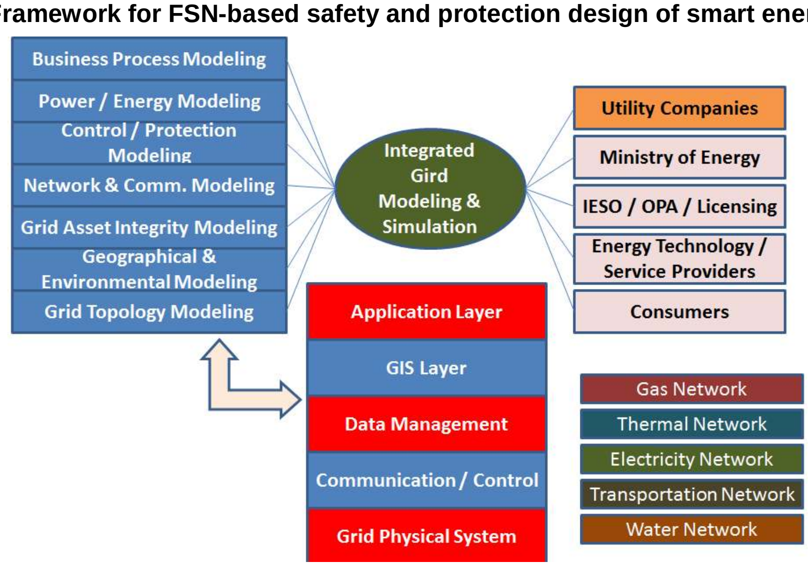

Fig. 11. The proposed information technological infrastructure of SEG/MEG integrated simulation environment

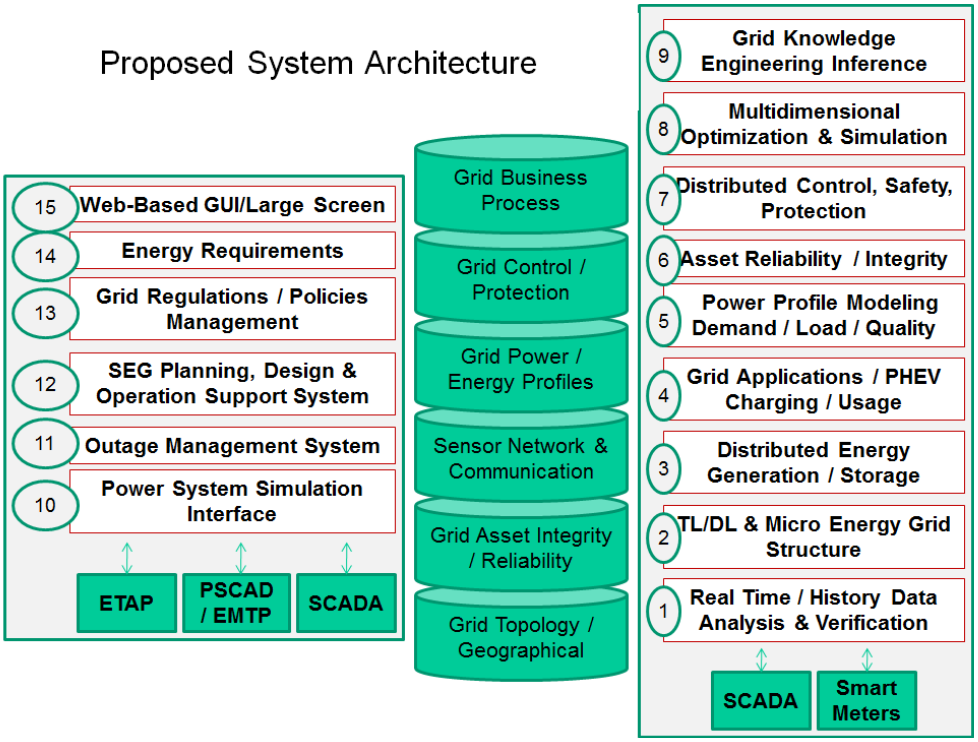

Fig. 12. System architecture of SEG simulation and planning tool

8. CONCLUSION

This paper presented overview of challenges and opportunities of smart energy grids and their implementation using adaptive modeling of energy grids using energy semantic networks (ESN). The proposed modeling technique is able to model interconnected micro energy grids (MEGs). In order to achieve resilient smart energy grids and micro energy grids, fault semantic networks (FSN) is proposed and framework is discussed. Safety and protection design framework is discussed to support resilient micro energy grids based on independent protection layers (IPLs) and fault semantic networks (FSN), which is employed to ensure resilient smart energy grids. The proposed design support tool will enable industry to migrate from current energy infrastructures to smart energy grids with dynamic and bidirectional energy supply, including different energy technologies from gas-power and renewable, as well as traditional fossil fuel.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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Peer-review history:
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http://sciencedomain.org/review-history/12080