Report for:

Energy Modelling Initiative – Bringing the Tools to Support Canada's Energy Transition
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Project Title:

A Cluster-Based load Model for a Resilient and Sustainable Community

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Contents

A Cluster-Based Load Model for a Resilient and Sustainable Community

Executive Summary

The proposed load model supports clean electricity utilization in a resilient system during severe climate conditions. While the existing load model aggregates all system components (loads, local generations, regulators, capacitors, etc.) at the customer or substation level, the proposed load model segregates load classes of different sizes, distributed energy resources (DERs) and energy storage systems (ESSs) to develop a multi-level model of demand/generation interaction that considers energy consumers/prosumers as customers. This new model uses the electricity demand/generation relationship among different customers (consumers/prosumers), sub-clusters, clusters, feeders and substations as well as the impact of DERs/ESSs at different levels. It enables the investigation of DER/ESS innovation deployment and requirement in demand/generation reliability and efficiency to support a low-carbon future. The proposed cluster-based load model also facilitates end-user engagement in energy efficiency programs and provides a support for policy-makers, energy market regulators and standard developers to accelerate deployment of clean energy technologies. As well, it facilitates policy pull to complement aggregator/end-user engagement with the required regulations and standards in a flexible and open market. This multi-level load model supports sustainable community development by providing a multi-level demand/generation relationship that opens new multi-size business opportunities for customers and community engagement as well as large investors to participate in different small/medium/large business activities. Overall, the proposed model is an essential tool for active electric distribution network that allows potential engineering and economic services, adds value to energy markets, and enables smooth integration and collaboration within the energy ecosystem.

1 Objective:

The objective of this project is to model distribution system loads in terms of a set of dynamic clusters that consider the stochastic nature of renewable energy resources, consumers/prosumers, critical loads, available energy storage, and end-user engagement as active participants in the energy market and energy efficiency programs. This cluster-based load model objective is supported by the following:

- **Escalating digitization within the active distribution network (ADN)**. Many intelligent network elements now have advanced sensors with real-time computational capability. Furthermore, the rapid advancement of IoT technologies and high-speed communication make it possible to drive the ADN as multi-level clusters that provide services to the electric grid and energy market. The smart grid transition can be enhanced by mapping the large power system into a set of smart clusters that have self-manageable, self-adequate, self-sufficient and self-healing features to drive low-carbon and cost-efficient assets and networks with a resilient capability under severe climate conditions.
- **A dramatic change in the structure of the power system**. Conventional loads are continuously changing with the emergence of new technologies. At the same time, there is a continual increase in the penetration level of distributed energy resources and energy storage systems. This change

emphasizes the use of different technologies concentrated at the grid-edge close to customer loads, which provide new energy services to a cluster of customers within a distribution network.

- **Customer engagement and consumer behavior is the focus of electrical utilities and the energy market**. The two activities have a varying relationship with a stochastic nature that impacts the load model. The main characteristics of these components can be accurately modelled at multi-level (end-user customer, sub-cluster/cluster/feeder/substation) rather than at the end-user level or aggregated at the substation level. Multi-level modelling enables mature interaction relationships among components, distributed DERs/ESSs, and loads.
- **The global electricity markets are enormous**. As technology deployment trends accelerate, the value of distributed assets and energy services can be fully implemented, managed, and smartly controlled in a cluster-based style instead of an aggregated component. The focus in the energy open market has great potential beyond estimating energy generation and consumption metrics. Rather, it has considered an electric asset-based model and strongly emphasized on customer-based models. Hence, zooming into cluster-based models provides the incentive for prosumers, consumers, and market players (commercial and industrial) to participate in an energy marketplace where customer engagement emphasizes that they are front and center in the energy market interests. Such clustering permits scalability that allows multiple marketplaces grow and to be established in parallel while the management of the ADN benefit from the impact of multi-level model data on consumer behavior, cluster and system performance. The deployment requirements of low-carbon cost-efficient networks and system needs will also be enabled.
- **Policies and regulations inhibit or accelerate technology trends**. In this case, for clean energy growth as well as resilient and sustainable communities, policies and regulations are not only an advantage but also a requirement. Policies and regulations differ from country to country and region to region. In general, the current policies, standards and energy market are in continuous evolution to adopt system changes and new technology deployment towards carbon-free resilient networks. Considering a cluster-based load model allows for a clear understanding of demand/generation interaction and the impact of clean technology deployment from end-user up to substation level. This understanding helps standard- and policy-makers and regulating authorities to implement a time-plan for developing upgraded versions that facilitate new opportunities for customers, communities, and third-party engagement.

2 Model Development:

The model is developed considering the following options:

1. Analytical model based on understanding the behaviour of different components in a cluster and their impacts on the cluster demand/generation.
2. Numerical model (Probabilistic model) based on data collected from measurements and simulations.
3. Numerical-Analytical integrated model

The power system utilizing this model is assumed flexible in size and operation and supports clean energy, AC/DC hybrid configurations, customer engagement and choices. Figure 1 shows a conceptual representation of a cluster-based load model as applied to a simulated version of the IEEE 123 system.

Sub-clusters (C1A, C1B, C1C, C1D), as illustrated in the figure, can be integrated to develop Cluster 1. The integration of adjacent sub-clusters from two different clusters are also presented (for example, C1C-C2C and C1B-C3A).

The load model maps system loads/nodes into a set of dynamic clusters of boundaries that are defined based on the capability of the available resources to provide a reliable energy service, load type/class, new business opportunities, or expected climate resilience level. The clusters' energy coverage is impacted by daily and seasonal demand/generation profiles as well as consumer behavior/activity and participation in the energy market.

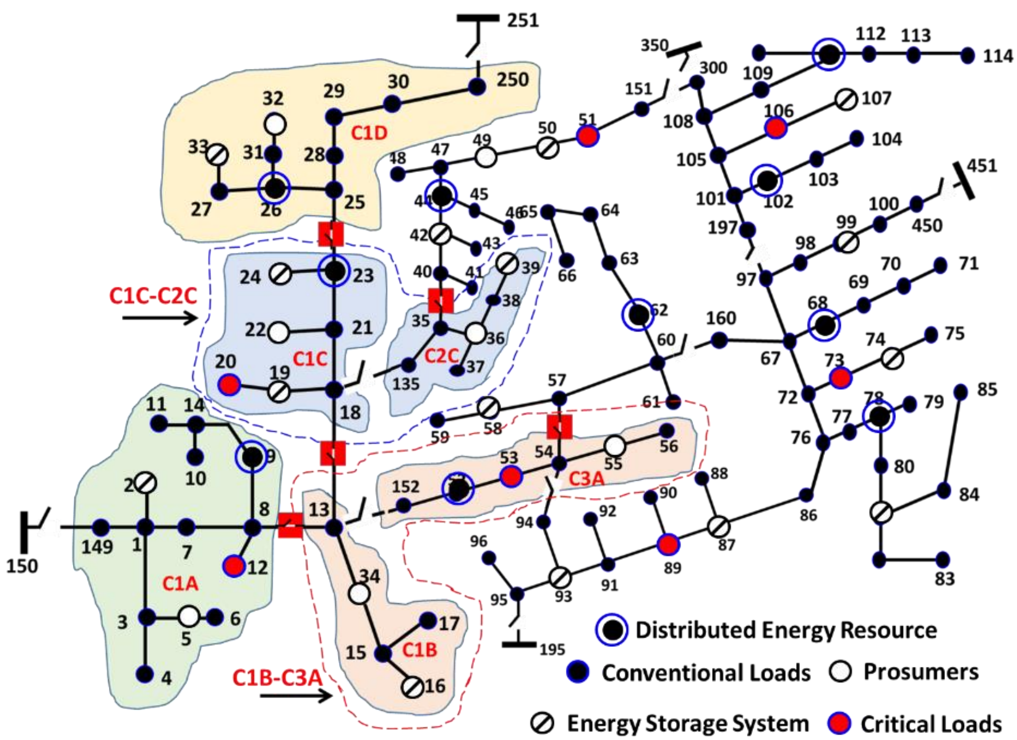


Figure 1: Simulated IEEE 123 system for modelling of different clusters and sub-clusters.

2.1 Model Nature and Cluster Development:

In the proposed project, the nature of the model is composed of clusters/sub-clusters with components consuming, storing, and generating energy. Their input/output relationship is influenced by both direct and indirect factors. The modelling accuracy is increased by gradually increasing the component size based on different engineering and/or business applications. Each cluster/sub-cluster may be developed from any of the following components:

1. **Cluster Load component**: This includes 3-phase and 1-phase motor loads, power electronic loads, static loads and critical loads. The load composition, time of use, power electronic interfacing and control, contactors and protection devices as well as voltage and frequency sensitivity are the main factors used to define the nature of this component. The load component size in the developed model is not only presented as a lumped (aggregated load) but is gradually increased to include:
    a. Single end-user
    b. Large load (industrial plants)

c. Critical loads (hospitals, data centers)
d. Cluster load level
e. Feeder load level
f. Substation load level

These loads are classified to serve residential, commercial, industrial, agriculture, critical-loads, transportation systems or mixed classes.

2. **Cluster DER component:** This includes fuel cells, wind turbines, solar photovoltaics (PV), and microturbines. Both DERs after the meter and before the meter are considered in the model, which is categorized as:
   a. Rotating machine-driven distributed generations.
   b. DC source-driven distributed generations.

   The model accuracy is enhanced by considering the following:
   a. Penetration level of variable renewable energy resources.
   a. Renewable energy and demand uncertainties.
   b. Isolated cluster DER survivability and resiliency.
   c. Maximum-coverage DER criterion (self-adequacy or self-sufficiency).
   d. Limited DER capacity and availability.
   e. Continuous operating time.
   f. DER dynamic or fixed cluster boundaries (isolation witches and automation level).
   g. Impact of grid flexibility, policies, incentives and aggregators on cluster generation-demand.
   h. Sensitivity of cluster to Transmission/Distribution interruptions.
3. **Cluster dispatchable/non-dispatchable generation component**: This includes diesel generator and natural gas generator as well as combined heat and power units. The following are considered to enhance the accuracy of the model:
   a. Percentage of dispatchable/non-dispatchable energy resources.
   b. Dispatchable/non-dispatchable generation capacity.
   c. Isolated cluster survivability and resiliency.
   d. Maximum-coverage criterion (self-adequacy or self-sufficiency).
   e. Limited generation capacity and fuel availability.
   f. Continuous operating time.
   g. Dynamic or fixed cluster boundaries (isolation witches and automation level).
   h. Impact of grid flexibility, policies, incentives and aggregators on cluster generation-demand.
   i. Sensitivity of cluster to Transmission/Distribution interruptions.
4. **Cluster electrical energy storage component:** This includes energy storage systems (ESSs) and electric vehicles (EVs). The following are considered to enhance the accuracy of the model:
   a. Penetration level of energy storage systems and electric vehicles.
   b. Impacts of incentives and policies on EVs/ESSs demand/generation profile.
   c. Impact of public charging networks on EVs/load profile.
   d. Impact of smart charging, vehicle-to-home (V2H) and vehicle-to grid (V2G).
   a. The impact of controlled/uncontrolled charging on electricity demand.
5. **Cluster end-user engagement program component**: While most energy utilities are new to the pursuit of customer engagement, many are exploring how to achieve it with their customers. Hence, this component is considered. It includes the following elements that have direct/indirect impact on the clusters' demand/generation relationship:
   a. Customer behavior
   b. Demand side management
      - Demand response
      - Energy efficiency program (EMS)

c. Aggregator/end-user interaction
d. Engagement in new business opportunities.

6. **Cluster system components**: This includes transformers, feeders, voltage regulators, load shedding and underfrequency/undervoltage, as well as other substations protection and control devices, etc.
7. **Policies and standards:** The indirect impact of this component on the cluster demand/generation model is considered.

2.2 Analytical-Based Model:

Figure 2 represents the cluster-based analytical load model. The analytical (component) load is an upgraded version of existing models, such as the complex load model (CLOD) and the composite load model [12, 21, 22, 23, 26, 27]. The model considers an active distribution network (ADN) with a significant amount of DERs, prosumers, ESSs, and conventional and controllable loads, as illustrated in Figure 1.

The model enables the modeling of the impact of control, protection, and power electronic interfacing devices for each component. The idea is to represent the dynamic nature of demand and generation and their impact on sensitive loads or during dropping and restart (or ride-through) under various operation conditions.

The impact of distributed energy resources, storage systems, and distribution system network's components is also considered in the multi-level load model.

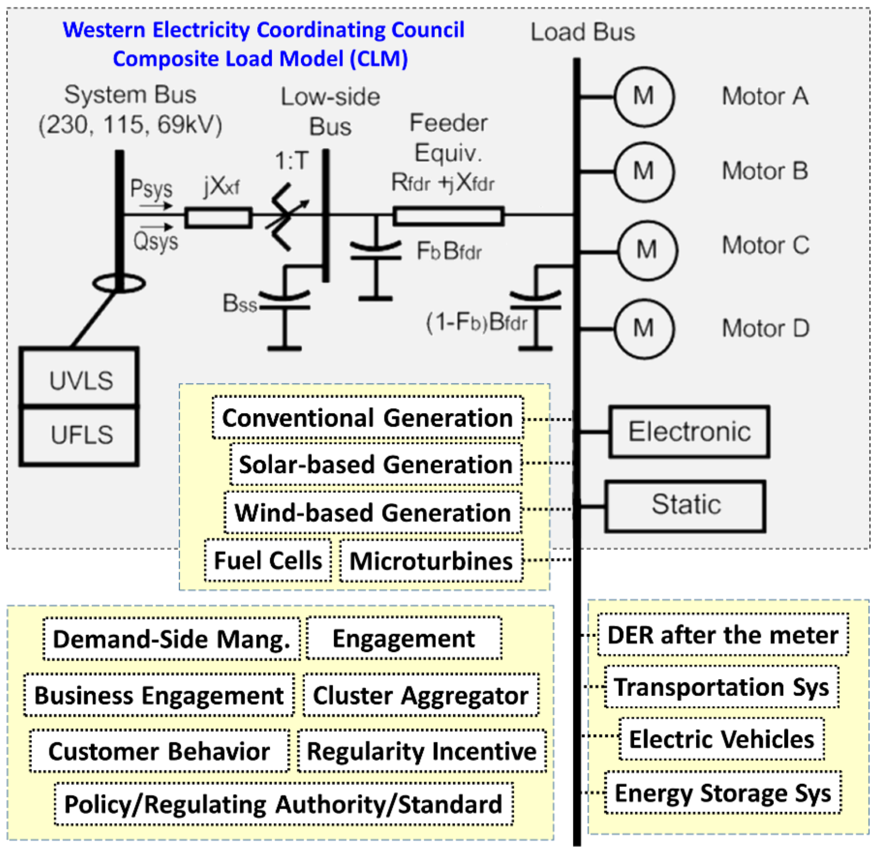


Figure 2: Cluster-based load model.

The stochastic nature of the demand/generation interaction is considered in the analysis in order to develop a probabilistic model within each cluster/sub-cluster and at the feeder or substation level. The indirect elements that may influence the demand/generation relationship are also integrated in the model. Considered as well are the impact of end-user behavior and/or engagement of energy efficiency and demand response programs, the influence of aggregators, new business opportunities, and developed policies, regularity incentives and standards.

Samples of end-use components in a commercial building, commercial sector and sector load break-down during summer peak are presented in Tables A1, A2 and A3 [23, 24]. ZIP models are used to describe the relationship between active and reactive power as well as the impact of voltage-frequency change on power. Parameters for this model are interpreted similar to those of the composite load model, considering constant impedance, constant current, motor loads, and the power electronics component of the load.

2.3 Type of Results in Analytical-Based Model:

The project model results have two forms:

- A mathematical relationship, which includes all the cluster demand/generation components that consider all influencing factors (direct/indirect).
- A cluster/sub-cluster load profile based on the deterministic or stochastic nature of the cluster components.

The initial results of the mathematical model (only demand) are considered in the following operation scenarios:

- **<u>Static characteristics of load model</u>**:
  Assuming the number of load-model component types is "*l*" and the number of end-use components in a building/sub-cluster/cluster is *k*, the mathematical representation of the demand of any end-use component (*k*) is:

$$P_{\mathrm{end-use,k}} = \sum_1^l \, (TOU_l\,) \propto_{k,l} P_{\mathrm{k}} \; [\, \mu_{1,l} \left(\frac{V}{V_o}\right)^{l,a1} + \mu_{2,l} \left(\frac{V}{V_o}\right)^{l,a2} + \mu_{3,l} \left(\frac{V}{V_o}\right)^{l,a3}](1 + K_{pf}\Delta f)\,] \tag{1}$$

The cluster load from any model component type (*l*) is:

$$P_{\mathrm{end-use},l} = \sum_1^k \, (TOU_l\,) \; \propto_{k,l} P_{\mathrm{k}} \tag{2}$$

The total cluster load of the composite components is:

$$P_{\mathrm{CL},total} = \sum_1^l P_{\mathrm{end-use},l} \left[\mu_{1,l} \left(\frac{V}{V_o}\right)^{l,a1} + \mu_{2,l} \left(\frac{V}{V_o}\right)^{l,a2} + \mu_{3,l} \left(\frac{V}{V_o}\right)^{l,a3} \right] (1 + K_{pf}\Delta f) \tag{3}$$

$$P_{\mathrm{CL},total} = \sum\nolimits_1^l \sum\nolimits_1^k (TOU_l\,) \left(\propto_{k,l}\right) P_{\mathrm{k}} \; \left[\mu_{1,l} \left(\frac{V}{V_o}\right)^{l,a1} + \mu_{2,l} \left(\frac{V}{V_o}\right)^{l,a2} + \mu_{3,l} \left(\frac{V}{V_o}\right)^{l,a3} \right] (1 + K_{pf}\Delta f) \tag{4}$$

$\mu_{1,l}, \mu_{2,l}, and\ \mu_{3,l}$ are the ZIP parameters, $\propto_{k,l}$ represents the percentage of the load model composition components, and TOU_l is the percentage of time of use component for each load model component type. The frequency deviation is $\Delta f = f - f_0$ and $K_{pf} = \frac{\partial P}{\partial f} = 0\ to\ 3.0$.

The equivalent circuit impedance of the three-phase induction motor is used to initialize the steady-state motor model. The reactive power consumption is defined based on the terminal voltage and active power load level, as well as the slip of the motor.

- **Dynamic characteristics of load model:**
  In a cluster-based model, a set of algebraic and differential equations is used to represent the motor behaviour. These equations are derived from the dynamic physical response of the motor components and the steady-state circuit model response.

- **Operational characteristics of load model:**
  The operational characteristics of some loads influence the dynamic response of the model. Type A motor, for example, can be categorized as 20% of larger 200-500 HP motors and have their first trip by the building energy management system (EMS) at 0.65 pu voltage after 100 ms. These motors are reconnected manually. On the other hand, 75% of small 10-25 HP A type motors have their trip by contactors at 0.50 pu voltage in less than 2 cycles. The contactors reclose at around 0.65 pu voltage within 100 ms, and the remaining 5% of the motors assume ride-through during disturbances. Table 1 presents a sample of industrial type A motor parameters. Similar characteristics are provided for other types of motors (B, C and D). The power electronic load component (PE) of the model represents an aggregate effect of their loads. The model assumes constant active and reactive power with unity power factor. The active and reactive PE load operational limits are defined by $V_{d1} \approx 0.7\,pu$ and $V_{d2} \approx 0.5\,pu$. The active and reactive power reduces linearly to zero consumption between voltages V_{d1} and V_{d2}. The PE load reaches zero when the voltage reduces below V_{d2}. All of the composite load parameters with sample values are listed in Table A.4.

Table 1: Sample of Industrial Motor A Load Parameters

Parameter	Define/Unit	Default
LfmA	Loading Factor [pu]	0.75
RsA	Stator Resistance [pu]	0.04
LsA	Stator Reactance [pu]	1.8
LpA	Transient Reactance [pu]	0.12
LppA	Sub-transient Reactance [pu]	0.104
TpoA	Transient OC Time Const [sec]	0.095
TppoA	Sub-transient OC Time Const [sec]	0.0021
HA	Inertia Constant [sec]	0.1
etrqA	Torque Speed Exponent	0
Vtr1A	Undervoltage Relay Trip 1 Vmag [pu]	0.65
Ttr1A	Undervoltage Relay Trip 1 Time [sec]	0.1
Ftr1A	Fraction of Motors w/ UV Trip 1 [pu]	0.2
Vrc1A	UV Reclose 1 Vmag [pu]	0.1
Trc1A	UV Reclose 1 Time [sec]	9999
Vtr2A	Undervoltage Relay Trip 2 Vmag [pu]	0.5
Ttr2A	Undervoltage Relay Trip 2 Time [sec]	0.02
Ftr2A	Fraction of Motors w/ UV Trip 2 [pu]	0.75
Vrc2A	UV Reclose 2 Vmag [pu]	0.65
Trc2A	UV Reclose 2 Time [sec]	0.1

2.4 Probabilistic-Based Model

Figure 3 shows the three stages of the probabilistic cluster-based modelling approach. Historical data are used as input to a data conversion stage. This stage is responsible for calculating the per-unit output/input power of the DERs/ESSs/demand components within a cluster and for conditioning these data to remove any outliers and interpolate any missing data. In the second stage, the extracted per-unit powers are then grouped based on the characteristics of DERS/ESSs/demand, class type, season, time of use, and day. For each group, the goodness-of-fit methodologies are used to obtain the best-fit probability density function (PDF) that accurately models the probabilistic behavior of the demand/generation relationship within a cluster.

Standardizing the historical data format is an essential requirement in order to automate the modelling engine. Historical data strings should contain the values of the variable parameter, time stamp, temperature, and generation type. The conditioned data is ready to be classified into groups of closely correlated points. The goodness-of-fit algorithms find the best-fit PDF to describe the probabilistic variables, i.e., the output/input power from the DERS/ESSs/demand in our model. The three stages result in the selected PDF and its parameters. Note that the grouping stage can output daily profiles for the DERS, ESSs, or demand.

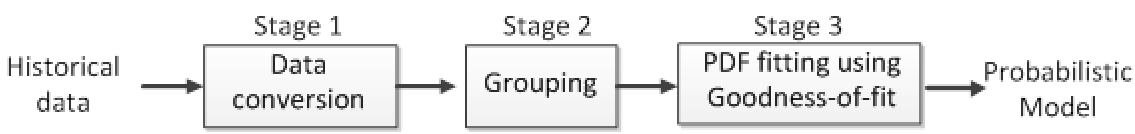


Figure 3: Probabilistic cluster-based modelling approach.

2.4.1 Data Conversion:

This stage depends on the probabilistic variable to be modelled. The functionality of the data conversion stage is to convert the given data into daily per-unit power profiles. The data conversion stage will be discussed in detail for each variable to be modelled.

2.4.2 Grouping:

The K-means unsupervised grouping technique [1] is used to group the power profiles into an unknown number of groups. Although the technique is unsupervised, as many types of renewable energy are highly dependent on the season, the number of groups is expected to be four (in case of wind) or five (in case of solar). The K-means grouping technique is based on minimizing the square of the error function presented in Equation (5).

$$\min\left(\sum_{j=1}^{k}\sum_{i=1}^{n} || x_i^j - c_j ||^2\right) \tag{5}$$

where $|| x_i^j - c_j ||$ is the distance between a data point x_i^j that belongs to group j and its centroid c_j. One advantage of this approach is the accurate grouping of profiles regardless of their time. In other words, if the day is a sunny day in winter and hence the wind profile is more like fall rather than winter, the grouping technique will group that day with fall days instead of winter days.

2.4.3 Goodness-Of-Fit:

The best-fit PDF can be selected using the well-known goodness-of-fit tests [2], [3]. These tests generally calculate a parameter called the test statistic, which is proportional to the error between theoretical (fitted) and experimental (historical) cumulative density functions (CDFs); hence, the PDF with the lower static is the one that better fits the historical data. If the available number of samples exceeds 2,000, both the Kolmogorov-Smirnov (K-S) test, as expressed by Equation (6), and the Anderson-Darling (A-D) test, as expressed by Equation (7), can be used to identify the best-fit PDF. The AD test is much more responsive to the tails of distribution, whereas the KS test is more responsive to the centre of distribution.

$$D = \max_{1 \le i \le n} \left(F(X_i) - \frac{i-1}{n}, \frac{i}{n} - F(X_i)\right) \tag{6}$$

$$A^2 = -n - \frac{1}{n} \sum_{i=1}^{n} (2i - 1)\left[\ln F(X_i) + \ln\left(1 - F(X_{n-i+1})\right)\right] \tag{7}$$

2.4.4 Parametric Density Estimation

Goodness-of-fit identifies the best probability density function that fits the given data set. An estimation of the PDF's parameters is carried out using the maximum likelihood (ML) estimation algorithm. Usually, it is convenient to maximize the log-likelihood function $L(\theta)$. The maximum log-likelihood estimation searches for the parameter $\hat{\theta}_{ML}$ which best represents the samples x, as shown in Equation (8):

$$\begin{gathered} \hat{\theta}_{ML} = argmax_{\theta\epsilon\Theta} \left(L(\theta)\right) \\ L(\theta) = \sum_{i=1}^{n} \log(p(x_i; \theta)) \end{gathered} \tag{8}$$

The ML estimate is obtained by finding the stationary point of the log-likelihood function, as follows:

$$\frac{\partial L(\theta)}{\partial \theta_j} = 0 \tag{9}$$

2.4.5 Wind-Based Generation Modelling

In most cases, wind speed is the recorded parameter which needs to be converted into per-unit power. The WECS characteristics [4] can be used for the conversion. The approximate relation between wind speed and output power can be expressed as in Equation (10):

$$P(v) = \begin{cases} 0 & 0 \le v \le v_{ci} \\ P_{rated} \times \dfrac{v - v_{ci}}{v_r - v_{ci}} & v_{ci} \le v \le v_r \\ P_{rated} & v_r \le v \le v_{co} \\ 0 & v_{co} \le v \end{cases} \tag{10}$$

The data structure required to establish the wind model and generate the daily profiles is given in tables 2 and 3:

Table 2: System Data for Wind-Based DER

P_{rated}	v_{ci}	v_{co}	v_r
Rated power (kW)	Cut in speed (m/s)	Cut out speed (m/s)	Rated speed (m/s)

Table 3: Data String for Wind-Based DER

Time	Wind Speed (m/s)	Ambient Temperature (℃)

In this way, wind speed data are converted into strings of per-unit powers with the time stamp and temperature. Afterwards, the data is organized as daily profiles to be propagated to the next stage. The wind data for two-successive years is used for developing the model in this report. The obtained daily profiles for the two years are grouped into four groups based on the season, as shown in Figure 4. The centroid of each group, obtained from the k-means technique, is highlighted in red. It is clear from the figures that the wind power has ultimate variability and is very stochastic (random) in nature. In addition, the centroid curve is not representative of the group, as it does not capture the wind variability within the season.

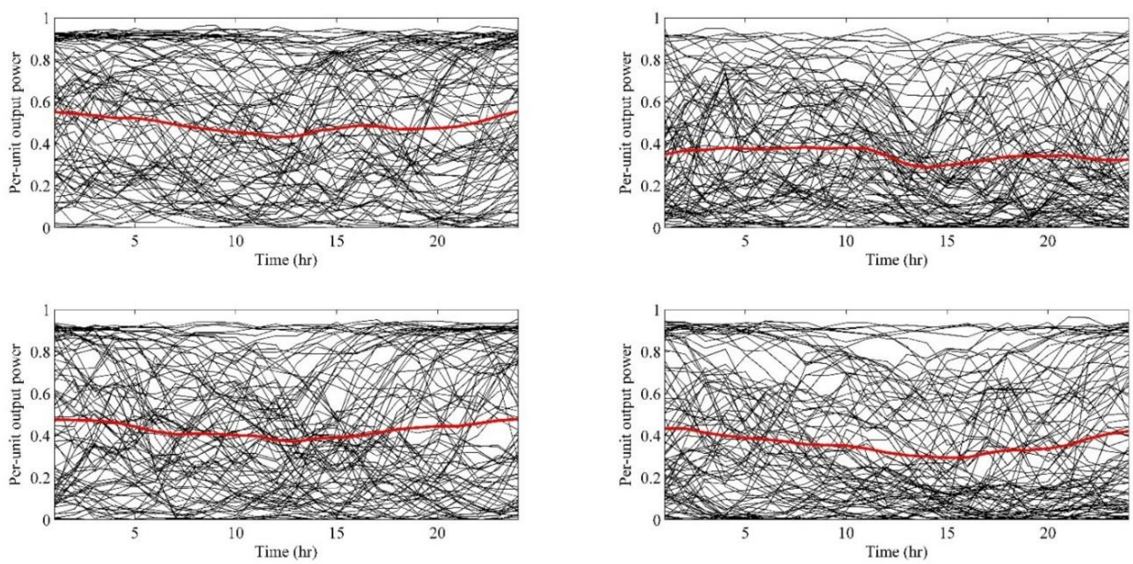


Figure 4: Seasonal-based grouping of two-year daily wind generation.

The approach recommended in this report for modelling of wind-based resources is the probabilistic approach. As denoted by stage 3 in the probabilistic modeling approach of Figure 3, a PDF fitting using the goodness-of-fit technique is used to establish the model. The probability distribution of the output power from wind for two-successive years and grouped based on seasons is shown in Figure 5.

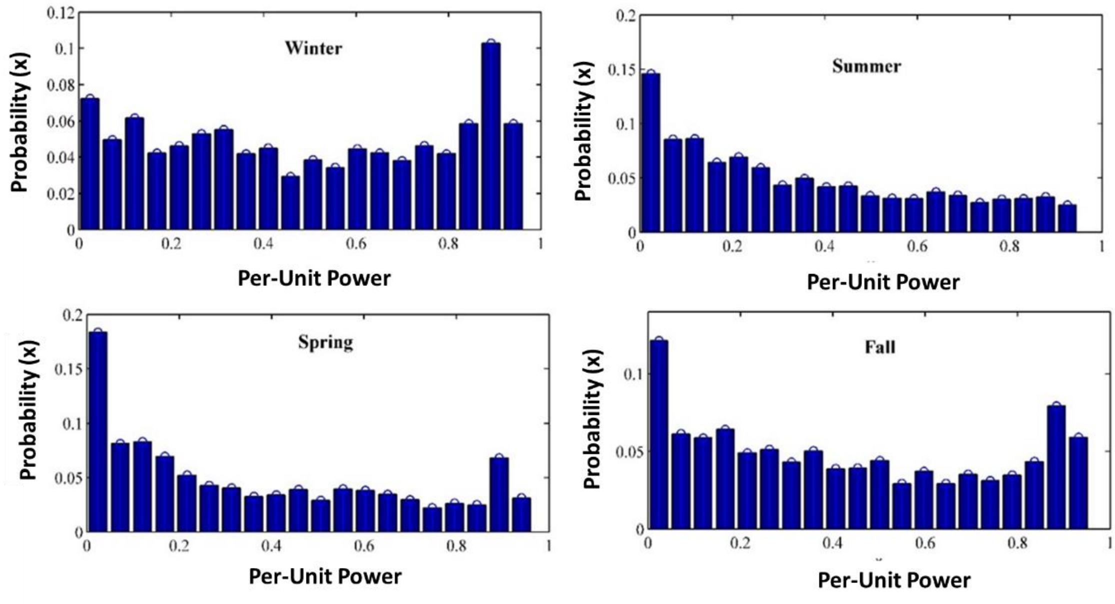


Figure 5: Seasonal-based probability distribution of two-year wind generation.

The aforementioned goodness-of-fit techniques are applied to these data and the results are presented in Table 4. For a detailed discussion of this part, please refer to Appendix B.

Table 4: Results of Goodness-Of-Fit Techniques

	Winter		Spring		Summer		Fall	
	K-S	A-D	K-S	A-D	K-S	A-D	K-S	A-D
Johnson-SB	**0.03228**	**46.181**	**0.03198**	**4.1535**	**0.02604**	**2.7687**	**0.03395**	**7.1416**
Weibull	0.10157	125.45	0.07846	247.45	0.06007	169.09	0.09065	190.33
Normal	0.08894	181.96	0.12714	71.088	0.10693	55.584	0.08715	49.691
Beta	0.08885	49.029	0.1624	115.69	0.15562	93.358	0.15671	114.28

As shown in Table 4, Johnson-SB is the best fit to the wind data, as it shows the least error in both tests (K-S and A-D). Therefore, the per-unit output power from wind-based resources can be modelled using the Johnson-SB PDF represented by Equation (11):

$$f(X) = \frac{\delta}{\lambda\sqrt{2\pi}z(1-z)} e^{\left(-\frac{1}{2}(\gamma+\delta\ln\left(\frac{z}{1-z}\right))^2\right)}, \qquad z = \frac{x-\zeta}{\lambda} \tag{11}$$

where γ and δ are shape parameters, λ indicates scale parameter, and ζ denotes location parameters.

The estimated values of the probability density function parameters using the aforementioned (ML) parametric density estimation are shown in Table 5.

Table 5: Wind Model Parameters

	Winter	Spring	Summer	Fall
γ	-0.01993	0.40832	0.48423	0.1866
δ	0.48906	0.46673	0.55561	0.49059
λ	0.95746	0.97881	0.97956	0.98015
ζ	0.00568	- 0.00765	- 0.00874	- 0.00616

2.4.6 Solar-Based Generation Modelling

In case of solar-based DERs, the solar irradiance and ambient temperature data are available with a time stamp. The data string required to establish the solar model is shown in Table 6.

Table 6: Data String for Solar-Based DER

Time	Solar Irradiance (kW/m^2)	Ambient Temperature (℃)

However, the system data availability depends on the knowledge of the system and can be divided into two scenarios, as presented in tables 7 and 8:

Table 7: System data for Solar-Based DER: Scenario 1

N	P_{rated}	V_{MPP}	I_{MPP}	V_{oc}	I_{sc}	K_i	K_v	N_{OT}	A
Number of cells per module	Rated power (kW)	Voltage at maximum power point (V)	Current at maximum power point (A)	Open-circuit voltage (V)	Short-circuit current (A)	Current temperature coefficients	Voltage temperature coefficients	Nominal operating temperature (℃)	Module area (m^2)

Table 8: System Data for Solar-Based DER: Scenario 2

η	$A\ (m^2)$
Conversion efficiency	Module area

The solar data and system data are used to calculate the solar output per-unit power using equations (12) [5] or (13) for system data scenarios 1 or 2, respectively.

$$
\begin{gathered}
T_c = T_A + s_a\left(\frac{N_{OT}-20}{0.8}\right) \\
I = s_a[\, I_{sc} + K_i(\, T_c - 25)] \\
V = V_{oc} - K_v \times T_c \\
P(s_a) = N \times FF \times V \times I \times A \\
FF = \frac{V_{MPP} \times I_{MPP}}{V_{oc} \times I_{sc}}
\end{gathered}
\tag{12}
$$

$$
(s_a) = \eta \times s_a \times A \times [1 - 0.005(\, T_A - 25)] \tag{13}
$$

The solar data is formatted as a string of the per-unit power with the time stamp and temperature. The data will then be organized as daily profiles to be propagated to the next stage. The obtained daily profiles for five successive years are organized into four groups based on the season, as shown in Figure 6. The centroid of each group obtained from k-means is highlighted in red. Similar to the wind data, it is clear from the figures that the solar power is very stochastic in nature. In addition, the centroid curve is not representative of the group, as it does not capture the solar variability within the season. In addition, the solar power is zero for a long time during the 24-hour period (prior to hour 5 and after hour 20). These periods should be excluded from the modelling, as the power is known to be zero and therefore the grouping and modelling will be for the non-zero power periods.

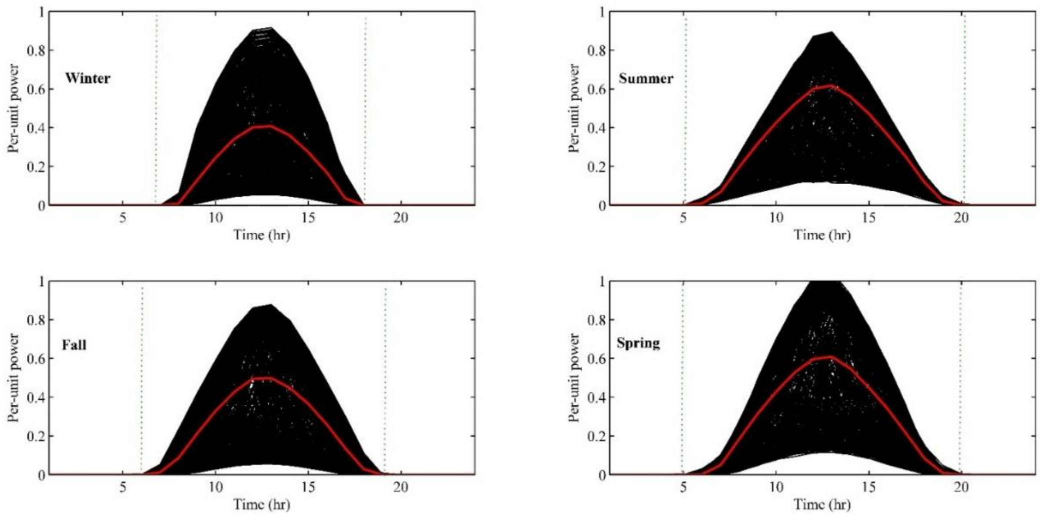


Figure 6: Seasonal-based grouping of five-year daily solar generation.

The solar per-unit output power is grouped into four seasons and the aforementioned goodness-of-fit techniques are applied to the solar data for each season. The results are presented in Table 9. The results show that if the K-S test is considered, the Johnson-SB is the best fit, while if the A-D test is considered, the Beta is the best fit. As mentioned earlier, the K-S test is more sensitive to the tails while the A-D test is more responsive to the center data. According to [6], the A-D test is more powerful than the K-S test, and thus the solar model selected in this report is based on the Beta distribution.

Table 9: Results of Goodness-Of-fit Techniques for Solar

	Winter Daytime		Spring Daytime		Summer Daytime		Fall Daytime	
	K-S	A-D	K-S	A-D	K-S	A-D	K-S	A-D
Johnson-SB	**0.04591**	354.2	**0.02509**	161.54	**0.04461**	65.941	**0.02478**	160.76
Weibull	0.11335	43.48	0.10136	33.344	0.10527	24.151	0.10642	34.182
Normal	0.1492	81.086	0.10495	41.778	0.08494	27.284	0.11095	48.747
Beta	0.08274	**27.957**	0.05783	**12.06**	0.07428	**8.2232**	0.04741	**12.517**

Based on the goodness-of-fit results, the Beta PDF expressed in Equation (14) is the solar model during different seasons, as follows:

$$f(X) = \frac{1}{\beta(\alpha_1,\alpha_2)} \frac{(x-a)^{\alpha_1-1}(b-x)^{\alpha_2-1}}{(b-a)^{\alpha_1+\alpha_1-1}}, \; a \le x \le b \tag{14}$$

where α_1 and α_2 are shape parameters, and a, b are boundary parameters. The estimated values of the PDF parameters using the aforementioned (ML) parametric density estimation are presented in Table 10.

Table 10: Solar Model Parameters

	Winter	Spring	Summer	Fall
α_1	0.7359	1.0875	1.4617	0.73811
α_2	1.2557	1.2697	1.3041	0.87307
a	0.01	0.04912	0.06654	0.0125
b	0.905	1.0403	0.88792	0.8775

2.4.7 Load Model

The load model is developed using the data given in the IEEE RTS [7]. According to the modelling approach presented in this report, load data is grouped into eight groups based on the season and day, a weekday or a weekend. The RTS data designate spring and fall as one season; consequently, the daily load curves are grouped into 6 different groups (3 seasons x 2 groups/season), as shown in Figure 7.

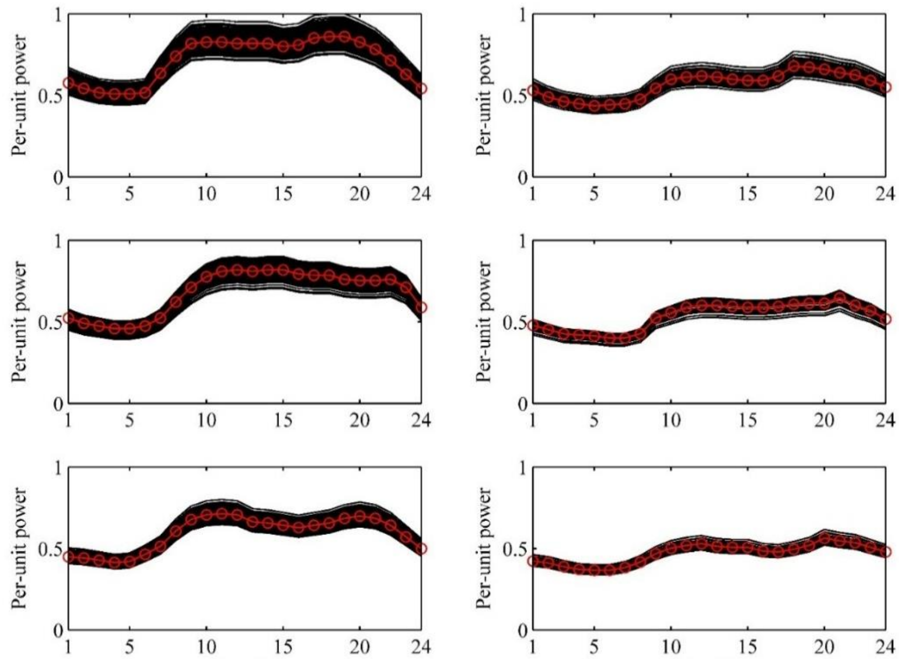


Figure 7: Seasonal-based grouping of daily load demand.

The k-means technique is usec the solar and wind power model, it is clear from the load profiles that the centroid is a good representative of the group. Therefore, the load demand can be modeled using the six load profiles presented in Table 11.

Table 11: Load Demand Profiles

	Winter		Spring/Fall		Summer	
Time (hr)	Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends
1	0.5764	0.5301	0.4495	0.4227	0.5233	0.4780
2	0.5420	0.4893	0.4423	0.4115	0.4906	0.4522
3	0.5162	0.4621	0.4281	0.3889	0.4743	0.4264
4	0.5076	0.4485	0.4138	0.3720	0.4579	0.4199
5	0.5076	0.4350	0.4209	0.3664	0.4579	0.4134
6	0.5162	0.4418	0.4637	0.3664	0.4743	0.4005
7	0.6366	0.4485	0.5137	0.3833	0.5233	0.4005
8	0.7398	0.4757	0.6064	0.4171	0.6215	0.4264
9	0.8172	0.5437	0.6778	0.4678	0.7114	0.5233
10	0.8258	0.5981	0.7063	0.5016	0.7768	0.5556
11	0.8258	0.6117	0.7135	0.5186	0.8095	0.5879
12	0.8172	0.6185	0.7063	0.5298	0.8177	0.6008
13	0.8172	0.6117	0.6635	0.5129	0.8095	0.6008
14	0.8172	0.5981	0.6564	0.5073	0.8177	0.5943
15	0.8000	0.5913	0.6421	0.5073	0.8177	0.5879
16	0.8086	0.5913	0.6278	0.4847	0.7932	0.5879
17	0.8517	0.6185	0.6421	0.4791	0.7850	0.5943
18	0.8603	0.6796	0.6564	0.4960	0.7850	0.6072
19	0.8603	0.6728	0.6849	0.5186	0.7605	0.6137
20	0.8258	0.6592	0.6992	0.5636	0.7523	0.6137
21	0.7828	0.6388	0.6849	0.5467	0.7523	0.6460
22	0.7140	0.6252	0.6421	0.5355	0.7605	0.6008
23	0.6280	0.5913	0.5708	0.5073	0.7114	0.5685
24	0.5420	0.5505	0.4994	0.4791	0.5887	0.5168

Errors between a specific group's centroid and all profiles belonging to this group are calculated. The probability density functions for these errors are shown in Figure 8. It is clear that the average error is almost zero with an error span range of $\pm$5% for all models except for winter weekdays, where the error spans a range of $\pm$10%. Error averages and standard deviations are calculated and presented in Table 12 for the six load models:

Table 12: Average and Standard Deviation of Error in Load Models

	Winter		Spring/Fall		Summer	
	Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends
μ	5.8600E-17	2.4779E-17	-3.4216E-17	2.1559E-17	-6.3215E-17	1.1921E-17
σ	0.04597	0.03354	0.02965	0.02064	0.03862	0.02747

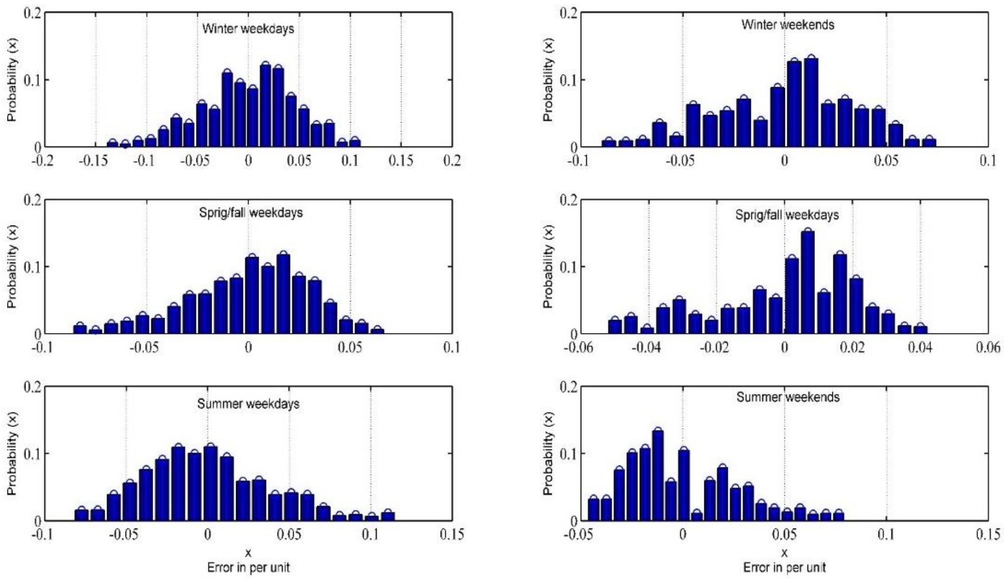


Figure 8: Probability distribution of load demand errors for different groups.

2.5 Energy Storage Probabilistic Model

As discussed earlier, renewable energy resources generally have a volatile and intermittent nature that imposes challenges for energy management. However, buffering this stochastic supply in an energy storage system (ESS) can offer a reliable constant supply and reduce supply uncertainty. The dispatch of the ESS is difficult because of the randomness of the ESS's state of charge (SoC). The ESS can be modelled as an energy queuing system that buffers renewable energy to offer a reliable and dispatchable supply to the system, as shown in Figure 9.

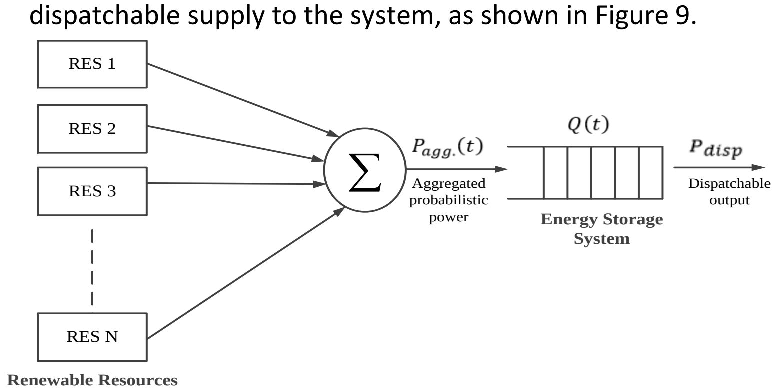


Figure 9: Layout of stochastic ESS model.

The change in the SoC of the ESS can be expressed by the stochastic differential Equation (15):

$$\frac{dQ(t)}{dt} = \begin{cases} P_{agg.}(t) - \frac{P_{disp}}{\eta} & , \ if \ P_{agg.}(t) > \frac{P_{disp}}{\eta} \ or \ Q(t) > 0 \ .0 \\ 0 \ , o.w. & \end{cases} \tag{15}$$

where η is the round trip efficiency of the ESS in charging and discharging. The CDF of the SoC can be approximated as presented in Equation (16):

$$P(Q(t) < x) \approx 1 - \frac{e^{-\frac{\theta^2}{2}}}{\theta\sqrt{2\pi}} e^{-\frac{2\sigma_{P_{agg}}\theta}{\epsilon} x} \tag{16}$$

$$, \theta = \sum \frac{\frac{P_{disp}}{\eta} - \mu_{P_{agg}}}{\sigma_{P_{agg}}} \tag{17}$$

2.6 Type of Results in Probabilistic-Based Model

The probabilistic model output is a probability density function (PDF) for the component's power. From this PDF, some useful information could be extracted, such as the most probable value, the variation range and corresponding probability, the level and range of confidence, and so on. In addition, these models could be integrated with the Monte Carlo simulation (MCs) [8] technique to form a probabilistic tool that injects into a study the risks and uncertainties of the models. The general steps for the MCs process using a model PDF are shown in Figure 10.

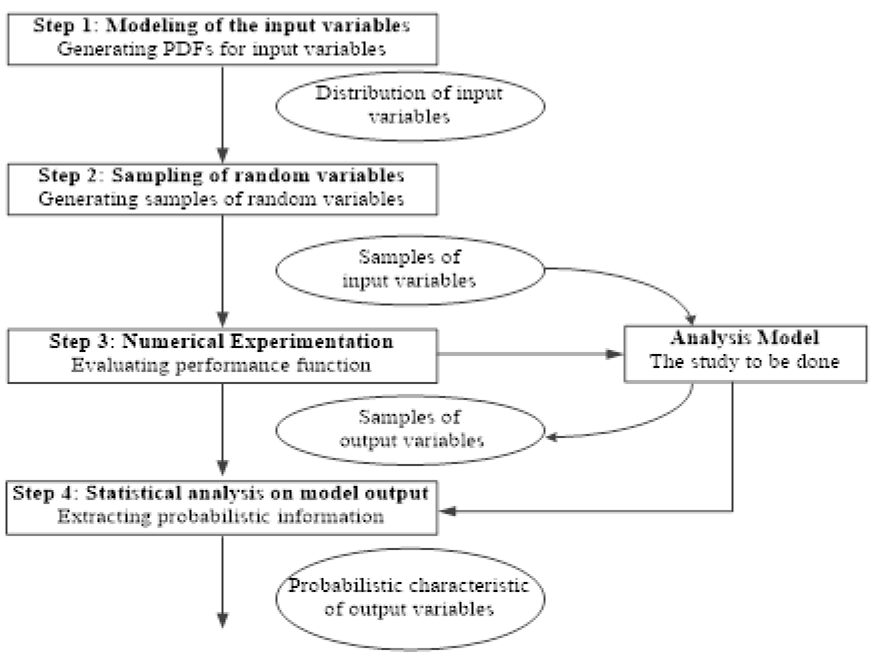


Figure 10: General steps for establishing a MCS-based probabilistic study.

3 Modelling Results

3.1 Cluster-Based Probabilistic Modelling

Figure 11 depicts a cluster of different generation/demand elements connected together through a network. Each individual element can be modeled using the probabilistic models derived in the previous section. However, these models need to be integrated together to form a cluster-based model. The possible scenarios obtained from the combination of the individual models to form the cluster-based model is listed in Table 13.

From the discussion of solar, wind, and demand modelling, it is clear that each component has different characteristics. The wind energy depends on the season, the solar energy is zero during nights, and load demand changes from weekdays to weekends. The initial stage of the cluster-based model is developed by combining these characteristics. Hence, the cluster is modelled using 16 different models for the 16 possible operation scenarios.

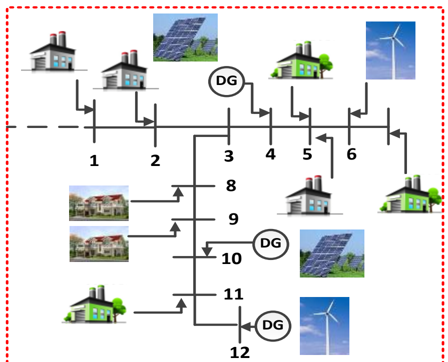


Figure 11: Generic cluster layout.

Table 13: Cluster-Based Models

Cluster Model #	Wind	Demand	Solar	Cluster Model Description
1	Spring	Weekday	Day	Spring/Weekday/Day-time
2			Night	Spring/Weekday/Night-time
3		Weekend	Day	Spring/Weekend/Day-time
4			Night	Spring/Weekend/Night-time
5	Fall	Weekday	Day	Fall/Weekday/Day-time
6			Night	Fall/Weekday/Night-time
7		Weekend	Day	Fall/Weekend/Day-time
8			Night	Fall/Weekend/Night-time
9	Winter	Weekday	Day	Winter/Weekday/Day-time
10			Night	Winter/Weekday/Night-time
11		Weekend	Day	Winter/Weekend/Day-time
12			Night	Winter/Weekend/Night-time
13	**Summer**	Weekday	Day	Summer/Weekday/Day-time
14			Night	Summer/Weekday/Night-time
15		**Weekend**	Day	Summer/Weekend/Day-time
16			**Night**	**Summer/Weekend/Night-time**

The proposed modeling framework is applied to the system shown in Figure 12. The Summer/Weekend/Night-Time model is considered as an example of cluster-based modelling.

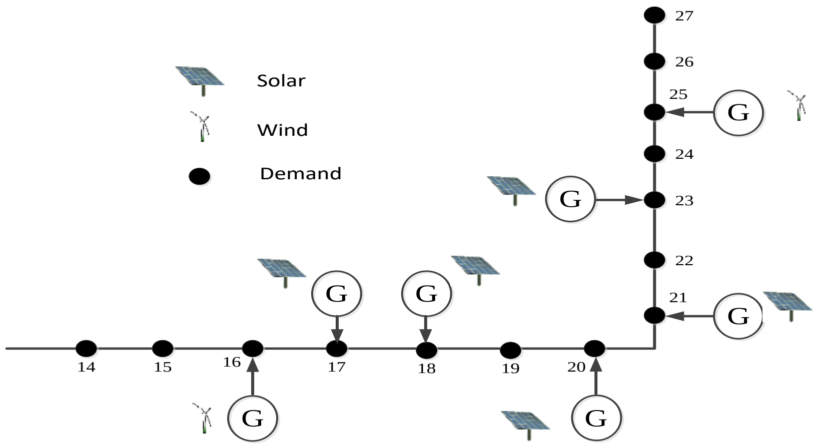


Figure 12: Sample cluster under study.

The probabilistic power flow described in [9-11] is used to calculate the power flow to/from the cluster. The resulting power flow data are given in Figure 13 in the form of a PDF.

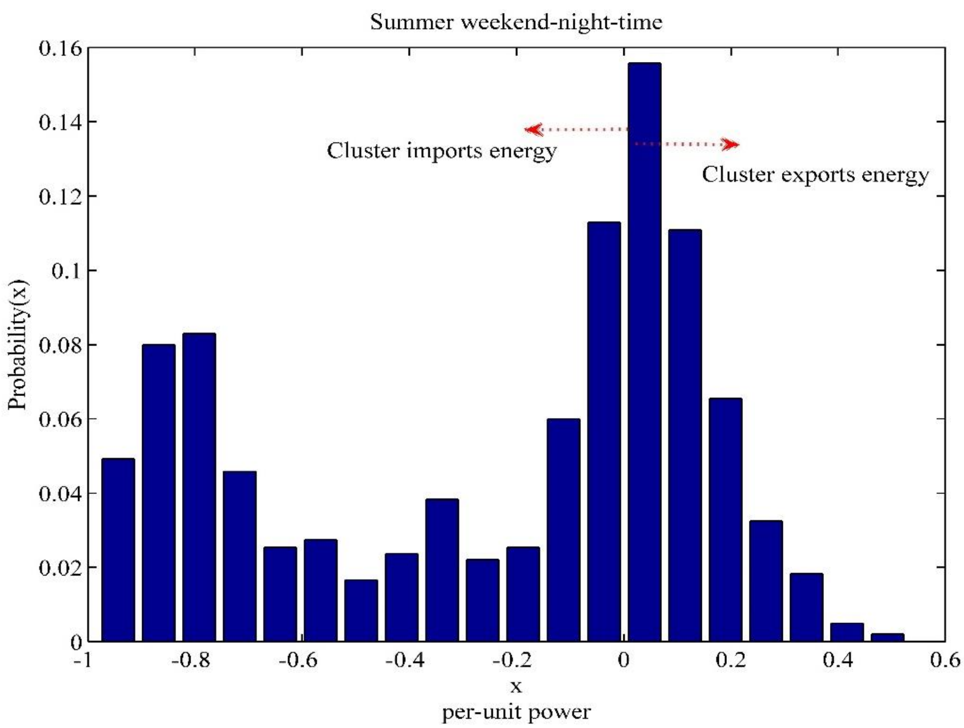


Figure 13: Per-unit power PDF for summer/weekend/night-time cluster model.

The best-fit PDF found for this model is based on the same procedures described earlier in the previous section and similarly the parameters are estimated using the ML estimation. The Johnson-SB described by Equation (11) is found to be the best-fit PDF for the cluster model. Model parameters are presented in Table 15:

Table 14: Cluster Model Parameters

Summer/Weekend/Night-Time Cluster Model			
γ	δ	λ	ζ
-0.34508	0.37567	1.1758	-0.9707

3.2 Cluster-Based Load Profile Model

Similar steps can be implemented to develop a daily-load profile for the cluster, rather than a PDF. Each cluster is also modelled for the same 8 possible operation scenarios (Day-time and Night-time are combined in case of a daily load profile). For each scenario, the components of the cluster are modelled using their 24-hr profile rather than their PDF. The conventional power flow to/from the cluster is calculated at each hour of the day and thus a daily-profile is obtained for the cluster. As an example, Figure 14 shows a sample of the per-unit daily power profile during summer/weekend for the cluster shown in Figure 12:

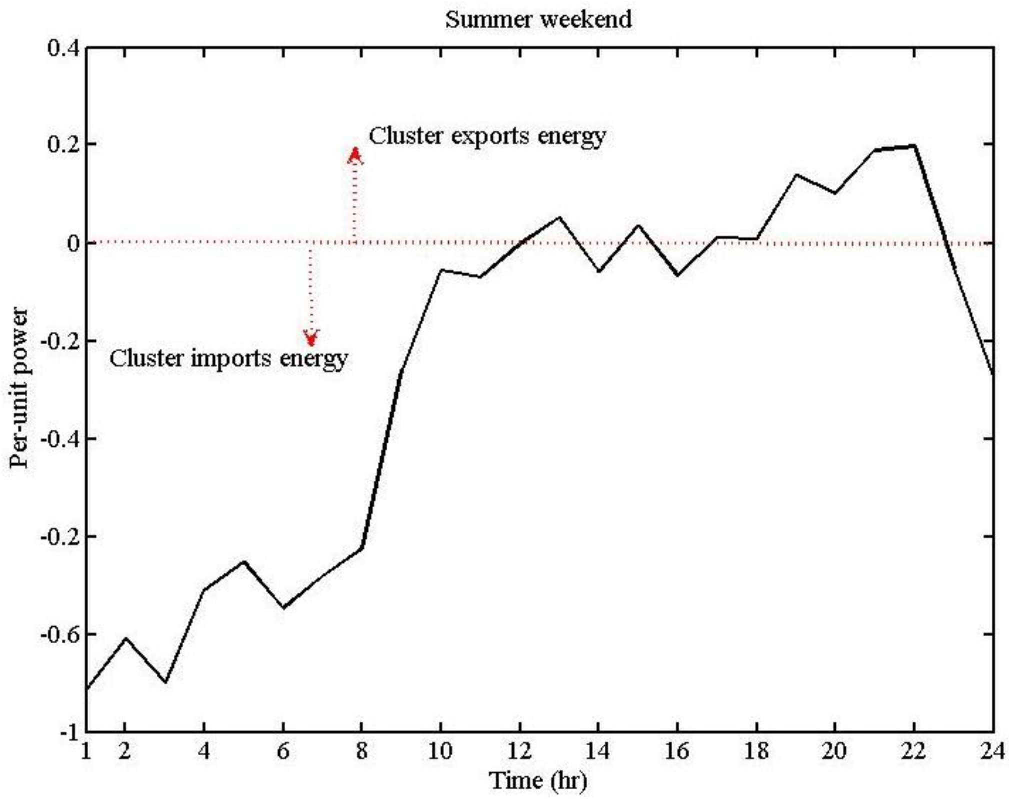


Figure 14: Cluster model based on the per-unit daily power profile for summer/weekend.

The probabilistic PDF model shown in Figure 13 can be used to estimate the probability of having energy surplus, deficiency, or adequacy within a cluster. The daily-profile model shown in Figure 14 identifies the time of day when these occasions occur.

3.3 Dynamic Nature of Cluster-Based Model (Continuous and future studies):

The proposed cluster-based load model increases the visibility of the effects of load response during steady-state and dynamic behavior. The objective is to ensure the ride-through of the DERS/ESSs and most of the loads, and to minimize the risk of additional motor stalling, generator tripping or voltage collapse. In order to illustrate the effect of motor stalling and tripping during faults, the response of load profile (P & Q) is simulated and compared with an aggregated load, as seen from the substation bus or at the C1A sub-cluster boundary. The voltage recovery at different locations show severe delayed voltage recovery and overshoot based on the load response and disturbance type.

The advantage of the proposed model comes from its ability to model the loads for different applications. Figure 15 shows the accuracy of the sub-cluster C1A load as compared with the substation lumped load (blue load profile) for different system topology. While supplying the system from node 150, the dynamic load at C1A boundary can be represented by the red load profile. As the configuration of the system changes (alternative source from node 135), the load profile at the C1A boundary changes to a black curve. These changes in the load profile are important for cluster-based application and end-user involvement. The data are also important for developing resilient systems that balance available DERs with the cluster load under steady-state and dynamic scenarios.

Figure 16 shows the voltage-frequency dependent load response during source disturbances. The cluster-based load response is impacted by voltage-frequency variation as well as the selection parameters of the model during dynamic and steady-state operation. Defining the impact of voltage-frequency variation on generation/demand components of a cluster is an important continuous research area for developing accurate dynamic and steady-state models.

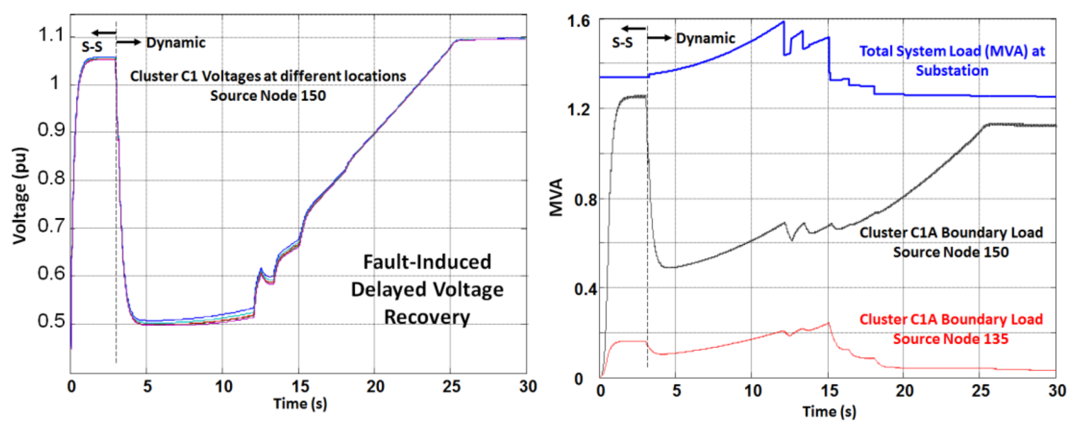


Figure 15: Variations in load clusters boundaries based on system disturbances during different system configurations.

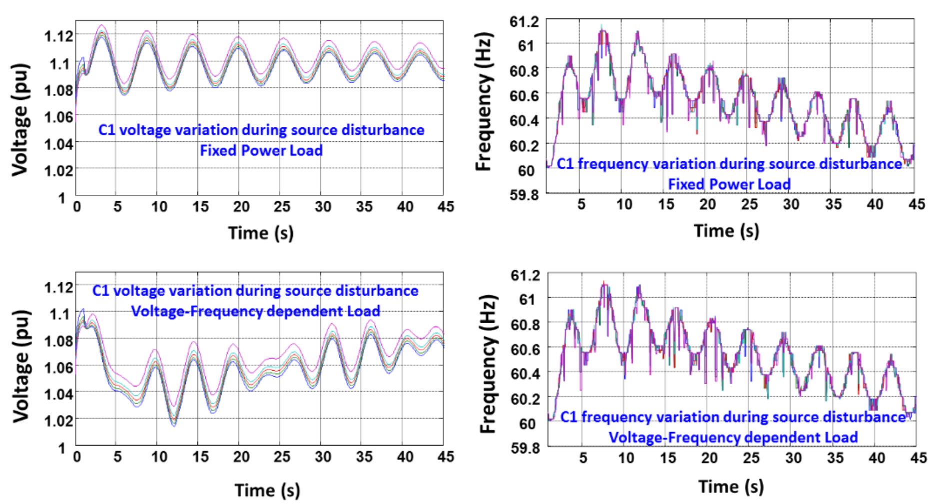


Figure 16: Voltage frequency-dependent load response during source disturbances (parameters selection dependent).

3.4 Mathematical Dynamic Model Parameters (Continuous and future studies):

Upgrading the developed mathematical models using different cluster components is an important research area. This includes steady-state and dynamic models. The modelling upgrade procedure involves the integration of measurement-based and component-based models for online development of a clustered based model. Reliable estimation considers cluster-based load model parameters, development of dynamic equivalents for clusters and sub-clusters, and validation of an equivalent cluster-based dynamic model of an active distribution network.

Figure 17 shows a simulated load model during steady-state and transient conditions. The model represents a distribution system load response to fault-induced voltage delay recovery. As can be seen, the dynamic behavior of the simulated load is modelled based on frequency voltage-dependent relations as well as the operation behavior of P.E., A, B, C and D motors response to voltage disturbance.

The selection of a mathematical model and the defining of its parameters for a cluster-based load model is an important continuous research area for our research team.

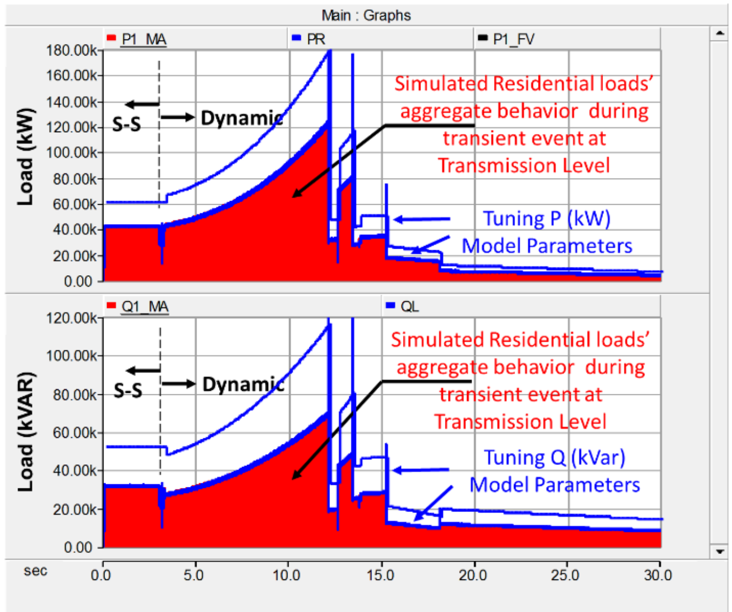


Figure 17: Tuning dynamic model parameters of simulated load during steady-state (S-S) and dynamic behavior.

3.5 Indirect Parameters of Cluster-Based Load Profile (Continuous studies):

Changes in policies/regulations and market energy designs are essential in order to be able to model and optimize the use of load/DERs/ESSs in an ADN. This model is also needed to include the indirect impact of customer behavior response to these policies and regulations. The model supports a multi-level understanding of the interaction between end-user customers and the grid and supports utilities in their effort to create engaged and loyal customers. It was reported in [29] that the Impacts of energy efficiency and DERs on electricity consumption in the USA indicate that a third of the states is already saving at least 1% of electricity consumption each year, while another third of the states—most of those being relatively new to energy efficiency—is saving between 0.25% and 0.75%. The proposed cluster-based load model supports the optimal locational placement of DERs/ESSs, defines limitations of DER/ESS penetration, and highlights benefits of community solar and storage systems. It also supports policy-makers and market designers to define strategies and approaches leading to optimal implementation of distribution upgrades and replacements for conventional utility investments. Developing a cluster-based load model and understanding the demand/generation relationship at multi-levels in an ADN has other indirect non-energy benefits, such as environmental benefits, health benefits, local economic development and lower maintenance costs.

Figure 18 presents the initial results of the steady-state load profile of each component model of the demand in the commercial sector presented in Table A2. The system is assumed operating at the rated voltage and frequency. End-user components are modelled and the load profile of each component is estimated using Equation (2), as illustrated in Figure 18. The model results are generated considering a conventional system (dark blue bars) and active distribution network with solar and wind DERs (light blue bars). This segregated model is important for studying the contribution of each component in the total aggregated demand to support equipment manufactures and policy-makers.

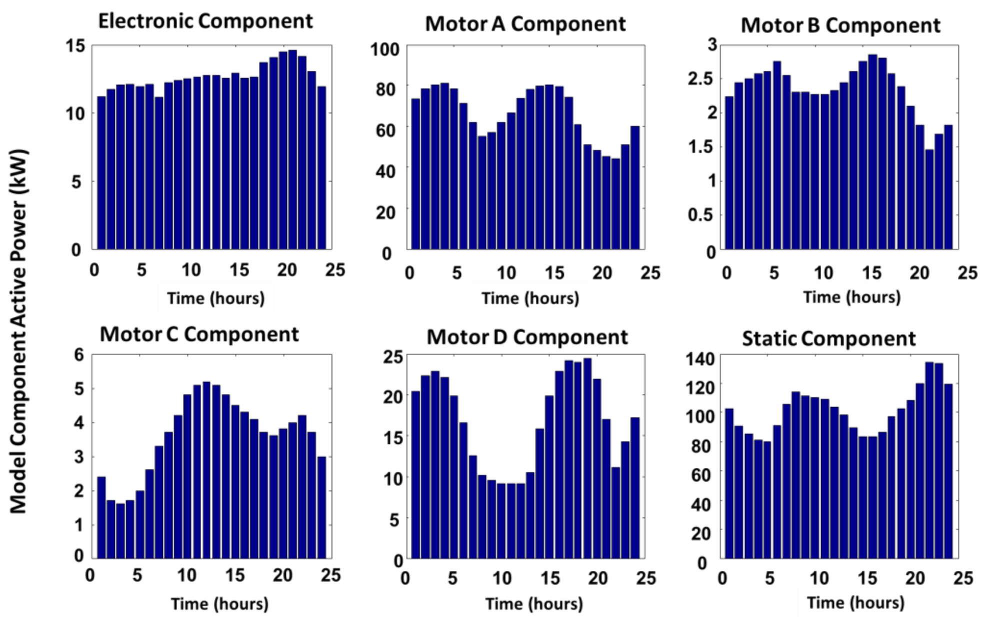
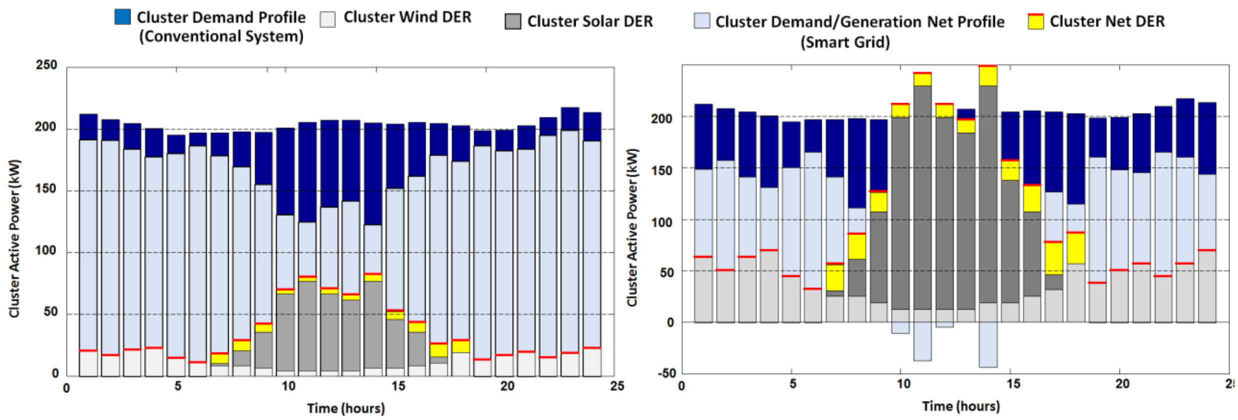


Figure 18: Steady-state load profile of each component model in commercial sector.

Two types of DERs—solar and wind—are considered in this sector, with low and high penetration. For low penetration, the solar type is assumed for all commercial classes with a rated power of 10% (30% for high penetration) of the demand, while the wind type is assumed for some sectors at 10% and 1.0% (30% and 3% for high penetration) for other commercial classes. These results support system designers to understand adequacy level, penetration limits, potential market benefits, and customer engagement. The total cluster demand/generation composite of all the components is estimated using Equation (4). The total DER contribution and demand during low and high DER penetration are estimated based on the time of demand/generation use as presented in Appendix A4 and as illustrated in Figure 19.



(a) (b)

Figure 19: Total cluster demand/generation composite of all components, (a) low DER penetration and (b) high DER penetration.

4 Modular Cluster-Based Load Model

The input/output relationship of the cluster-based load model is presented in Figure 20. Based on the application and type of results, different modules are activated. The model can operate as a standalone or as an integrated part to feed other applications within a complete system. The demand-generation functions are flexible and can be updated to accommodate other existing load models. It is also can be integrated in the ecosystem for business or engineering applications.

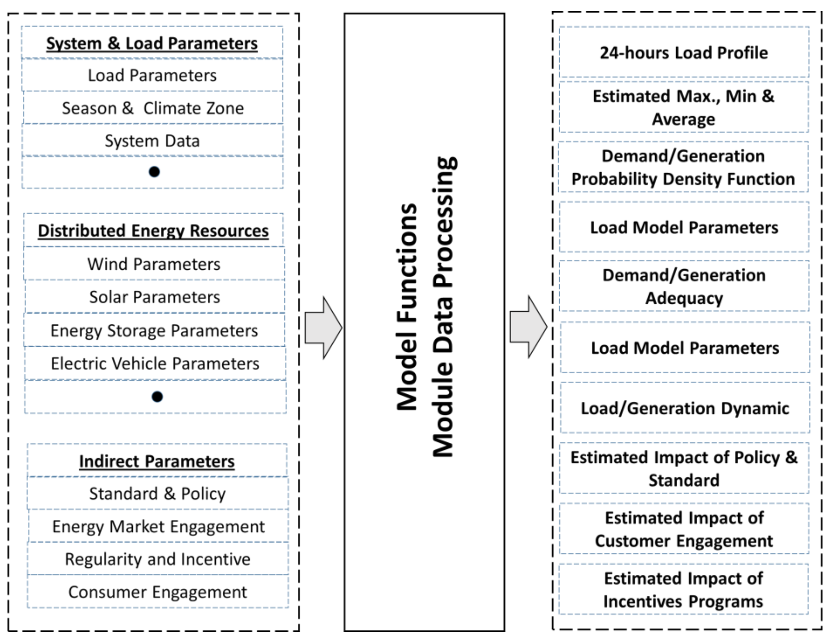


Figure 20: Modular representation of input/output relation

Figure 21 shows a conceptual representation of the data requirements for a component load model. The total system load model component (demand, generation, storage, engagement, and behavior) composition is continuously changing. Each cluster/sub-cluster has a different composition that should be aggregated or disaggregated based on the modelling level and application (steady-state and dynamic).

Hence, the load model data should be comprehensive in order to represent the effect of the cluster's components on the load profile. While the size of the data is large at the substation and feeder level, it is manageable at the cluster/sub-cluster level.

The aggregated load is decomposed into a set of load components of different load classes. The model parameters are derived for each component localized at a certain building/class-type in terms of fractions of load composition. All the composite load parameters with sample values are listed in Table A4. The impact of season, climate zone, time of day, DERs/ESSs, consumer behavior and engagement are considered.

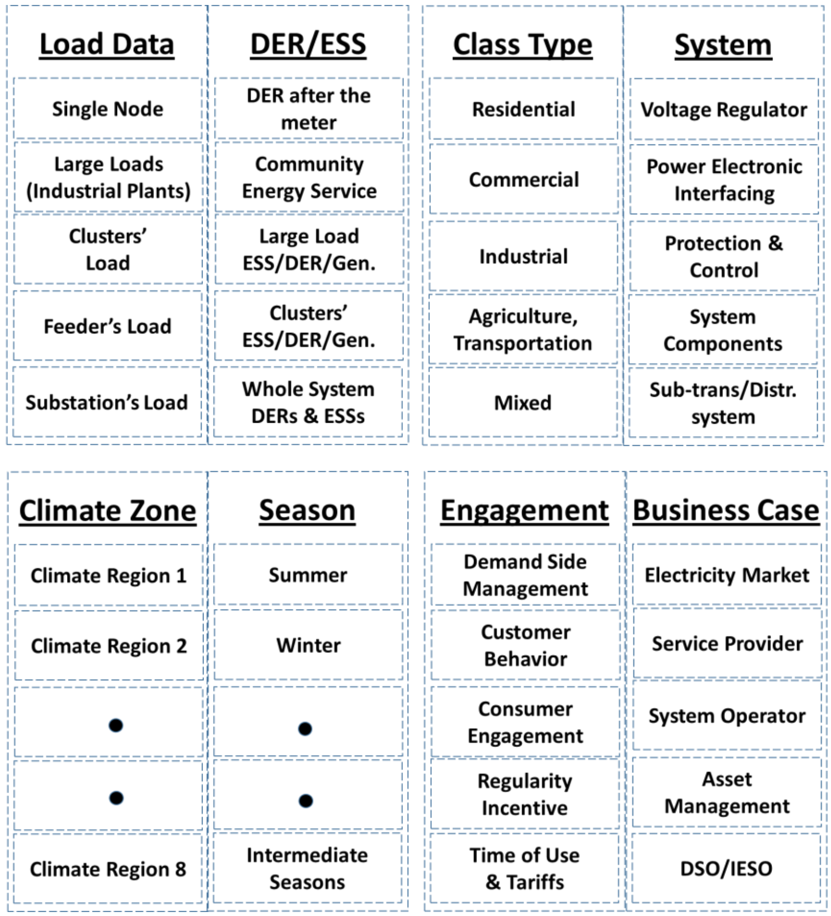


Figure 21: Conceptual representation of data requirement for component load model.

5 Other Models with Similar Objectives

5.1 Available Models

Load modeling is a challenging task due to the large number of diverse load components, the lack of precise load composition information, and the stochastic, time-varying, weather-dependent and consumer behavior-dependent nature. Different load models are reported in the literature and they primarily fall into two main categories: measurement-based (Numerical – load characteristics) or component-based (Analytical – physical-based modeling) [12, 25-27]. Both measurement-based and component-based models aim to develop accurate load modelling during static and dynamic operations.

Among the static models is the ZIP model, which represents the relationship between the voltage magnitude and power in a polynomial or exponential equation that combines constant impedance (Z), current (I), and power (P) components. Other models include the impact of frequency to develop voltage and frequency dependent models [12, 13, 19, 25-27]. In the dynamic models, active and reactive power is represented as a function of past and present voltage magnitude and frequency [12, 13, 19, 25-27]. These models are used to represent the power responses to step disturbances of the bus voltage and frequency variations. They are commonly employed to represent loads that slowly recover over a period of time ranging from several seconds to tens of minutes. The ZIP model and induction motor model (IM), exponential recovery load model (ERL), Siemens PTI PSS/E Complex load model (CLOD) and Western Electricity Coordinating Council (WECC) CLM have been developed to model power system loads, with an emphasis on the dynamic behavior of the loads [12, 13, 19, 15-27]. In general, WECC load models focus on the component-based approach, while EPRI-developed hybrid approaches integrate measurement- and component-based load models.

The integration of renewable DERs/ESSs and the implementation of demand-side management (demand response and energy efficiency programs) as well as the development of a resilient system prompted by current and anticipated severe changes in climate conditions highlights the need for more detailed modeling of the loads. This need is emphasized in active distribution networks (ADN) with a significant amount of DERs/ESSs, high penetration of EVs, and controllable loads that allow small-scale systems (microgrids) to operate in either grid-connected or islanded modes.

Intensive research in the literature has focused on providing aggregated models for the entire network using black-box [13-15] and grey-box [15-18] approaches. A mathematical relationship is developed to relate the input to the output without considering any physical structure. Another area of research focuses on modelling the static and dynamic behavior of directly coupled and inverter-coupled DERs [13, 15, 17, 18]. However, the lack of inherent machine dynamics (inertia characteristics for inverter-coupled DERs) and control dynamics of the power electronic devices present a challenging task for dynamic modelling. Several studies focus on developing a dynamic circuit model for fuel cells and battery energy storage systems (BESS) [12].

5.2 Comparison with Other Models with Similar Objectives:

Compared with other models with similar objectives, this project has the following aims:

1. We intend to develop a load model that considers the stochastic nature of conventional load data, DER/ESS, class type, system components, climate zones, season, customer engagement and behavior, and business opportunities. The developed cluster's load model could be presented as a probability density function, maximum values, or average values of load profiles based on steady-state or dynamic engineering applications as well as other business opportunities inside or outside the energy market.

2. The load is modelled at different levels and not only as an aggregate model at the substation bus. While the current design of the grid makes it difficult to decarbonize the power sector, even as new renewable generation is added, the cluster-based modelling supports the development of a resilient system. Cluster-based modelling allows the stochastic nature of DERs/ESSs/EVs to be balanced with each cluster's load for different periods of time, seasons or climate zones, hence enabling the de-carbonization of the power sector. Multi-level load modelling facilitates the development of a time-synchronization map of demand/generation relationship during different operation conditions within different clusters. This helps build a demand/generation survivability time duration relationship for control/protection actions within a resilient system. It also permits scalability that allows multiple marketplaces to be established and grow in parallel.

3. Understanding the demand/generation relationship at a cluster level as well as their dynamic response promotes business opportunities that support the energy market to develop a resilient and sustainable community. It reduces barriers and facilitates the optimal coupling of electric demand/generation relationship with other participant within the ADN in order to assess, generate, store, trade, and utilize energy efficiently. It also encourages cluster-owner (and third-party) investment to develop new business cases. This includes investing in the required technologies or upgrading DER/ESS deployment for developing self-adequate, self-sufficient, standalone, decarbonized, secure and resilient clusters at the lowest cost and highest reliability.

4. The developed model is customer behavior-driven, demand response-enabled, and consumer engagement-motivated. The cluster-based load model links the technical domains to the services that consumers and third parties can provide to one another and to the electric power system. The modelling problem is partitioned from the end-user load to cluster level and then up to the feeder and substation levels. This gradual modelling provides opportunities to motivate end-user and aggregator participation in a wide range of opportunities, from trans-active energy and asset management at the end-user level to energy market participation and storage system investment at the sub-cluster/cluster/system level.

5. This load model seeks to pinpoint the main characteristics of modern loads and their emerging technologies, considering the full potential of an Active Distribution Networks in an open market that supports customer engagement and choice. Within each cluster, the generated energy is distinct, whether it is immediately consumed or stored for future work. This distinction allows consumption priority with assigning value (critical loads) within a resilient system. In addition, this comprehensive understanding of consumed and stored energy within the multi-level load model brings up-to-date system load/generation/storage relationships for policy-makers, energy regulators, and standard-developer organizations.

6. The model is flexible in nature and harmonized with the electricity market. It supports flexibility in electricity supply and demand, and considers the dynamic and steady-state stochastic nature of demand/generation response. Furthermore, it supports end-user and aggregator engagement and provides a means to achieve a fully decentralized operation with peer-to-peer trading partners at the core of an expanding ecosystem. It can be utilized as a standalone or integrated with other modules to provide different inputs for power and energy system programs (dynamic or steady state) for wholesale market, service providers and DSO/IESO applications such as those listed in Table 16.

Table 15: Samples of Standalone and Integrated Application of Load Model

Applications	Single End-Use	Industrial Plant	Critical Load	Cluster Load	Feeder Load	S/S Load
Transactive Energy Market	*	*	*	*	*	*
Asset Management	*	*	*	*	*	*
Energy Efficiency/Demand Response	*	*	*	*	*	*
Volt/VAr Control & Power Quality	*	*	*	*	*	*
Optimal Reconfiguration				*	*	*
Contingency Analysis (DS)				*	*	*
Switch Order Management				*	*	*
Dispatcher Training Simulator		*		*	*	*
Resiliency & Reliability	*	*	*	*	*	*
Load/DER/ESS Forecasting		*		*	*	*
Day Ahead & Hour Ahead		*	*	*	*	*
Peak-Load Shaving, Load Shifting		*		*	*	*
Renewable Optimization	*	*	*	*	*	*
Load-Generation Imbalance	*	*	*	*	*	*
Frequency Regulation		*		*	*	*
Ancillary Services	*	*	*	*	*	*
First-Swing & Small-Signal		*		*	*	*
Synchronizing Power & Stability		*		*	*	*
Cold-Load Pickup		*		*	*	*
Dynamic Overvoltages				*	*	*

5.3 Model limitations

The size of the data required for accurate modelling is an essential challenge in developing the model. The input data changes according to different factors, either direct or indirect. Some of these factors change with time, region, and load class type and require continuous updating until saturated. Other factors are indirect and depend on customer engagement, customer behavior, and implemented policies and standards. These changes require continuous monitoring and updating to match different applications.

5.4 Policies and Current Model

Government policies and regulations play a major role in promoting clean energy growth and resilient and sustainable communities. Due to the nature of these technologies, policies, standards and energy markets are in continuous evolution to adopt system changes and new technology deployments. These policies aim to establish carbon-free resilient networks.

Load models such as the one presented in this proposal will help policy-makers and regulating authorities to implement a time plan for developing new policies that facilitate new opportunities for customers, communities, and third-party engagement.

The detailed and comprehensive models for loads, generations and stored energy resources make the up-to-date system component relationships readily available for policy-makers, energy regulators and standard-developer organizations to define strategies and approaches that will lead to least-cost implementation for distribution upgrades and replacements for conventional utility investments.

In the following sections, a brief summary on the benefits and applications of the proposed load model to policy-makers is outlined:

Government:

- The model will assist government and policy-makers to determine the best energy mix strategy for the country.
- The model will assist government and policy-makers to determine the impact of greenhouse gas emission reduction on the electricity sector.
- The model will assist government and policy-makers to set the guidelines for improving energy efficiency in the country.
- The model will assist government and policy-makers to determine the best energy market strategies and rules.
- The model will assist government and policy-makers to regulate the role of the electric energy storage in the electric power systems.
- The model will assist government and policy-makers to regulate the effect of electric vehicles on the electric energy system in the country.

Utilities:

- The model will support utilities to establish proper policies for resource planning for generation, transmission and distribution.
- The model will enable utilities to design policies for operation incentives based on detailed and accurate cost-of-service.
- The model will provide utilities with the proper tool to design suitable demand management measures in order to delay building new infrastructures.
- The model will empower utilities to accurately monitor their reliability indices and trends.
- The model will assist utilities to determine with great certainty the best penetration levels of renewable energy resources on their systems.

Customers:

- The model will enhance customer choices and opportunities.
- The model will help track customer behavior changes and their impact on electricity consumption.
- The model will promote customer choice for adopting greenhouse gas emission reduction technologies.

6 Possible Future Studies

6.1 Dynamic nature of a cluster-based model under voltage-transients, voltage oscillations, and frequency oscillations.

6.2 Develop an on-line numerical-analytical integrated model.

6.3 Investigate the dynamic nature of cluster-based load models in reference to the IEEE std. 1547 (2018).

6.4 The indirect impact of cluster customer engagement, customer behavior, policies and standards on the cluster's demand/generation relationship.

6.5 Utilizing the UW power and energy labs for developing an integrated dynamic model for DERs/ESSs/Demand.

1. References

[1] A. Likas, N. Vlassis, and J. J. Verbeek, “The global k -means clustering algorithm,” Elsevier Pattern Recognit. Soc., vol. 36, no. 1, pp. 451–461, 2003.

[2] B. W. Woodruff, A. H. Moore, E. J. Dunne, and R. Cortes, “A Modified Kolmogorov-Smirnov Test for Weibull Distributions with Unknown Location and Scale Parameters,” IEEE Trans. Reli., vol. R-32, no. 2, pp. 209–213, 1983.

[3] T. W. Anderson and D. A. Darling, “A Test of Goodness of Fit,” J. Am. Stat. Assoc., vol. 49, no. 268, pp. 765–769, 1954.

[4] J. Hetzer, D. C. Yu, and K. Bhattarai, “An Economic Dispatch Model Incorporating Wind Power,” IEEE Trans. Energy Convers., vol. 23, no. 2, pp. 603–611, Jun. 2008.

[5] Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, and R. Seethapathy, “Optimal Renewable Resources Mix for Distribution System Energy Loss Minimization,” IEEE Trans. Power Syst., vol. 25, no. 1, pp. 360–370, Feb. 2010.

[6] Razali, N. M., & Wah, Y. B., Power comparisons of Shapiro-Wilk , Kolmogorov-Smirnov , Lilliefors and Anderson-Darling tests. Statistical Modeling and Analytics, vol. 2, no. 1, pp. 21–33, (2011).

[7] "Reliability Test System Task Force The EEE Reliability Test System-1996 a report prepared by the Reliability Test System Task Force of the Application of Probability Methods Subcommittee", IEEE Trans. on Power System, vol. 14, pp. 1010-1020, Aug. 1999.

[8] E. McGrath and D. Irving, Techniques for Efficient Monte Carlo Simulation. Volume II. Random Number Generation for Selected Probability Distributions. US: National Technical Information Service, 1973.

[9] M. E. Nassar and M. M. A. Salama, "A novel probabilistic load model and probabilistic power flow," 2015 IEEE 28th Canadian Conference on Electrical and Computer Engineering (CCECE), Halifax, NS, 2015, pp. 881-886.

[10] M. E. Nassar and M. M. A. Salama, "Probabilistic power flow using novel wind and solar probabilistic models," 2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, 2016, pp. 1-5.

[11] M. E. Nassar and M. M. A. Salama, "Adaptive Self-Adequate Microgrids Using Dynamic Boundaries," in IEEE Transactions on Smart Grid, vol. 7, no. 1, pp. 105-113, Jan. 2016.

[12] Anmar Arif, Zhaoyu Wang, Jianhui Wang, Barry Mather, Hugo Bashualdo, and Dongbo Zhao, “Load Modeling—A Review,” IEEE Transactions on Smart Grid, VOL. 9, NO. 6, Nov. 2018

[13] X. Feng, Z. Lubosny, and J. Bialek, “Dynamic equivalencing of distribution network with high penetration of distributed generation,” in *Proc. 41st Int. Univ. Power Eng. Conf.*, Newcastle Upon Tyne, U.K., 2006, pp. 467–471.

[14] X. Feng, Z. Lubosny, and J. W. Bialek, “Identification based dynamic equivalencing,” in *Proc. IEEE Lausanne Power Tech Conf.*, Lausanne, Switzerland, 2007, pp. 267–272.

[15] P. N. Papadopoulos *et al.*, “Black-box dynamic equivalent model for microgrids using measurement data,” *IET Gener. Transm. Distrib.*, vol. 8, no. 5, pp. 851–861, May 2014.

[16] F. O. Resende and J. A. P. Lopes, “Development of dynamic equivalents for microgrids using system identification theory,” in *Proc. IEEE Lausanne Power Tech Conf.*, Lausanne, Switzerland, 2007,pp. 1033–1038.

[17] S. M. Zali and J. V. Milanovi´c, “Generic model of active distribution network for large power system stability studies,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3126–3133, Aug. 2013.

[18] J. V. Milanovi´c and S. M. Zali, “Validation of equivalent dynamic model of active distribution network cell,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2101–2110, Aug. 2013.

[19] IEEE Task Force on Load Representation for Dynamic Performance, “Load representation for dynamic performance analysis (of power systems),” *IEEE Trans. Power Syst.*, vol. 8, no. 2, pp. 472–482, May 1993.

[20] Y. Ge *et al.*, “An event-oriented method for online load modeling based on synchrophasor data,” *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 2060–2068, Jul. 2015.

[21] P. Regulski, D. S. Vilchis-Rodriguez, S. Djurovi´c, and V. Terzija, “Estimation of composite load model parameters using an improved particle swarm optimization method,” IEEE Trans. Power Del., vol. 30, no. 2, pp. 553–560, Apr. 2015.

[22] J.-K. Kim et al., “Fast and reliable estimation of composite load model parameters using analytical similarity of parameter sensitivity,” IEEE Trans. Power Syst., vol. 31, no. 1, pp. 663–671, Jan. 2016.

[23] NERC, Dynamic Load Modeling Technical Reference Document, December 2016, [Online]. Available: https://www.nerc.com/comm/PC/LoadModelingTaskForceDL/Dynamic%20Load%20Modeling%20Tech %20Ref %202016-11-14%20-%20FINAL.PDF

[24] William Gifford et al., End-use data development for power system load model in New England, Methodology and Results, Lawrence Berkeley National Laboratory, April 10, 2014, [Online]. Available: https://certs.lbl.gov/sites/all/files/data-development-for-ne-end-use-load-modeling.pdf

[25] CIGRE WG C4.605 Recommendations on Measurement Based and Component Based Load Modelling Practice- 2012, [Online]. Available: https://www.researchgate.net/publication/260266835_CIGRE_WG_C4605 _Recommendations_on_Measurement_Based_and_ Component_Based_Load_Modelling_Practice

[26] IEEE Task Force on Load Representation for Dynamic Performance, “Standard load models for power flow and dynamic performance simulation,” IEEE Trans. Power Syst., vol. 10, no. 3, pp. 1302–1313, Aug. 1995.

[27] IEEE Task Force on Load Representation for Dynamic Performance, “Bibliography on load models for power flow and dynamic performance simulation,” IEEE Trans. Power Syst., vol. 10, no. 1, pp. 523–538, Feb. 1995.

[28] Lisa Schwartz et al., Electricity End Uses, Energy Efficiency, and Distributed Energy Resources, Energy Analysis and Environmental Impacts Division, Lawrence Berkeley National Laboratory, 2017, [Online]. Available:https://www.energy.gov/sites/prod/files/2017/02/f34/Electricity%20End%20Uses%2C%20Ene rgy %20Efficiency%2C%20and%20Distributed%20Energy%20Resources.pdf

Appendix A:

Table A1: Samples of End-Use Components in Commercial Building

Building Type	End Use	Electronic	Motor-A	Motor-B	Motor-C	Motor-D	ZIP (Ip)	ZIP (Iq)	ZIP Zp	ZIP Zq
Large Office	Heating		0.7			0.2			0.1	0.02
	Cooling		1							
	Vent	0.3		0.7						
	Water Heather								1	0.15
	Cooking	0.2		0.2					0.6	
	Refrigeration	0.1	0.8			0.1				
	Exterior Lighting						1	-0.36		0.06
	Interior Lighting						1	-0.36		0.06
	Office Equipment	1								
	Miscellaneous			0.5	0.5					
	Process	0.5		0.25	0.25					
	Motors		0.3	0.4	0.3					
	Air Compression		1							

Table A2: Samples of Load Components in Commercial Sector (Sub-cluster)

Historical Rated phase Power (kW)	End Use	Sector Class	Electronic	Motor-A	Motor-B	Motor-C	Motor-D	ZIP (I)	ZIP (Z)	DER (PV)	DER (Wind)
150	Air Compression	All commercial classes	0	1	0	0	0	0	0	1	0.1
45	All Other End Uses - COM	Healthcare	0.2	0	0	0	0	0	0.8	0	1
70	Cooking	All commercial classes	0.1	0	0.05	0	0	0	0.85	1	0.1
100	Elevator drives and hydraulic pumps	All commercial classes	0	0	0	1	0	0	0	1	0.1
55	Lighting - CFL/Linear Fluorescent	All commercial classes	0	0	0	0	0	1	0	1	0.1
45	Lighting - HID Interior	All commercial classes	0	0	0	0	0	0	1	1	0.1
35	Lighting - Incandescent	All commercial classes	0	0	0	0	0	0	1	1	0.1
25	Lighting - Other	All commercial classes	0	0	0	0	0	0	1	1	0.1
25	Office Equipment	All commercial classes	1	0	0	0	0	0	0	1	0.1
50	Refrigeration	Lodging	0.1	0.4	0	0	0.5	0	0	0	1
25	Refrigeration	Healthcare	0.2	0.7	0	0	0.1	0	0	0	1
55	Refrigeration	All commercial classes	0.1	0.8	0	0	0.1	0	0	1	0.1
40	Space Cooling - Single Phase	All commercial classes	0	0	0	0	1	0	0	1	0.1
50	Space Cooling - Split Phase	All commercial classes	0	0	0	0	1	0	0	1	0.1
50	Space Cooling - Three Phase	All commercial classes	0.15	0.85	0	0	0	0	0	1	0.1
200	Space Heating	Healthcare	0	0.75	0	0	0.15	0	0.1	0	1
250	Space Heating	All commercial classes	0	0.7	0	0	0.2	0	0.1	1	0.1
35	Ventilation	All commercial classes	0.3	0	0.7	0	0	0	0	1	0.1
35	Water Heating	All commercial classes	0	0	0	0	0	0	1	1	0.1

Table A3: Samples of Sector-Demand Breakdown (Cluster)

	All Sectors %							
	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	Region 7	Region 8
Electronics	18	16	14	17	16	14	15	16
Motor A	14	18	15	15	16	15	17	16
Motor B	12	12	13	12	12	13	11	12
Motor C	6	7	8	9	8	7	10	7
Motor D	25	23	25	19	18	26	19	23
Constant Current	12	12	10	12	13	11	12	12
Constant Impedance	13	13	14	17	17	14	16	14

Table A4: Time of Use

Hour	P.E	Motor A	Motor B	Motor C	Motor D	Static (Cur)	Static (RES)	DER (PV)	DER (Wind)
1	0.15	0.122	0.080	0.024	0.101	0.025	0.36	0	0.5
2	0.157	0.131	0.087	0.017	0.11	0.02	0.32	0	0.4
3	0.161	0.134	0.089	0.016	0.113	0.015	0.3	0	0.5
4	0.162	0.135	0.092	0.017	0.109	0.02	0.285	0	0.55
5	0.16	0.131	0.093	0.02	0.098	0.0225	0.28	0	0.35
6	0.162	0.119	0.098	0.026	0.082	0.025	0.32	0	0.25
7	0.149	0.103	0.091	0.033	0.062	0.03	0.37	0.1	0.2
8	0.164	0.092	0.082	0.037	0.05	0.035	0.4	0.2	0.2
9	0.166	0.095	0.082	0.042	0.047	0.04	0.39	0.35	0.15
10	0.167	0.103	0.081	0.048	0.045	0.045	0.385	0.65	0.1
11	0.169	0.111	0.081	0.051	0.045	0.05	0.38	0.75	0.1
12	0.171	0.123	0.083	0.052	0.045	0.055	0.36	0.65	0.1
13	0.171	0.130	0.087	0.051	0.052	0.05	0.34	0.6	0.1
14	0.168	0.133	0.093	0.048	0.078	0.045	0.31	0.75	0.15
15	0.173	0.134	0.098	0.045	0.098	0.0425	0.29	0.45	0.15
16	0.168	0.132	0.102	0.043	0.113	0.0415	0.29	0.35	0.2
17	0.169	0.124	0.100	0.041	0.119	0.04	0.3	0.15	0.25
18	0.184	0.102	0.092	0.037	0.118	0.0385	0.34	0.1	0.45
19	0.189	0.085	0.085	0.036	0.121	0.035	0.36	0	0.3
20	0.194	0.080	0.075	0.038	0.108	0.0375	0.38	0	0.4
21	0.196	0.075	0.065	0.04	0.084	0.039	0.42	0	0.45
22	0.19	0.074	0.052	0.042	0.055	0.04	0.47	0	0.35
23	0.175	0.085	0.060	0.037	0.07	0.035	0.47	0	0.45
24	0.16	0.100	0.065	0.03	0.085	0.03	0.42	0	0.55

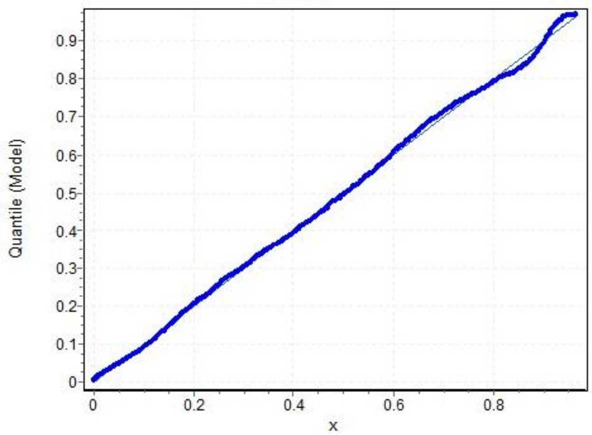
Table A5: List of WECC Composite Load Model Parameters with Example Values [REF]

Feeder		Electronic Load		Motor B		Motor C		Motor D	
Bss	0	Fel	0.167	FmB	0.167	FmC	0.167	FmD	0.167
Rfdr	0.04	Pfel	1	MtypB	3	MtypC	3	MtypD	1
Xfdr	0.05	Vd1	0.75	LFmB	0.8	LFmC	0.8	LFmD	1
Fb	0.75	Vd2	0.65	RsB	0.03	RsC	0.03	CompPFD	0.97
Xxf	0.08	Frcel	0.25	LsB	1.8	LsC	1.8	VstallD	0.6
Tfixhs	1	**Motor A**		LpB	0.16	LpC	0.16	RstallD	0.1
Tfixls	1	FmA	0.167	LppB	0.12	LppC	0.12	XstallD	0.1
LTC	1	MtypA	3	TpoB	0.1	TpoC	0.1	TstallD	0.02
Tmin	0.9	LFmA	0.7	TppoB	0.0026	TppoC	0.0026	FrstD	0
Tmax	1.1	RsA	0.04	HB	1	HC	0.1	VrstD	0.9
step	0.00625	LsA	1.8	EtrqB	2	EtrqC	2	TrstD	0.4
Vmin	1	LpA	0.1	Vtr1B	0.5	Vtr1C	0.5	FuvrD	0.17
Vmax	1.02	LppA	0.083	Ttr1B	0.02	Ttr1C	0.02	Vtr1D	0.65
Tdel	30	TpoA	0.092	Ftr1B	0.2	Ftr1C	0.2	Ttr1D	0.02
Tdelstep	5	TppoA	0.002	Vrc1B	0.65	Vrc1C	0.65	Vtr2D	0.9
Rcmp	0	HA	0.05	Trc1B	0.6	Trc1C	0.6	Ttr2D	5
Xcmp	0	EtrqA	0	Vtr2B	0.7	Vtr2C	0.7	Vc1offD	0.4
Static Load		Vtr1A	0.75	Ttr2B	0.02	Ttr2C	0.02	Vc2offD	0.4
Pfs	-0.99	Ttr1A	1	Ftr2B	0.3	Ftr2C	0.3	Vc1onD	0.45
P1e	2	Ftr1A	0.2	Vrc2B	0.85	Vrc2C	0.85	Vc2onD	0.45
P1c	0.54546	Vrc1A	0.9	Trc2B	1	Trc2C	1	TthD	30
P2e	1	Trc1A	1	Th1tD	0.3				
P2c	0.45454	Vtr2A	0.5	Th2tD	2.05				
Pfrq	-1	Ttr2A	0.02	TvD	0.025				
Q1e	2	Ftr2A	0.47						
Q1c	-0.5	Vrc2A	0.639						
Q2e	1	Trc2A	0.73						
Q2c	1.5								
Qfrq	-1								
MBase	0								

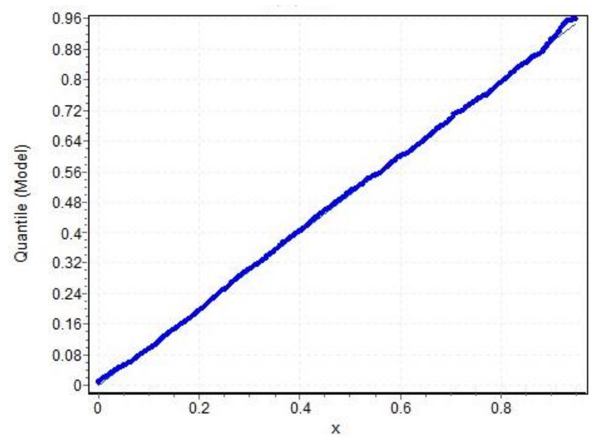
Appendix B:

QQ plot: This plot shows the relation between the data and the fitted model. The ideal scenario when the data matches the model and therefore the ideal Q-Q plot is a straight line with a 45^{o} slope.

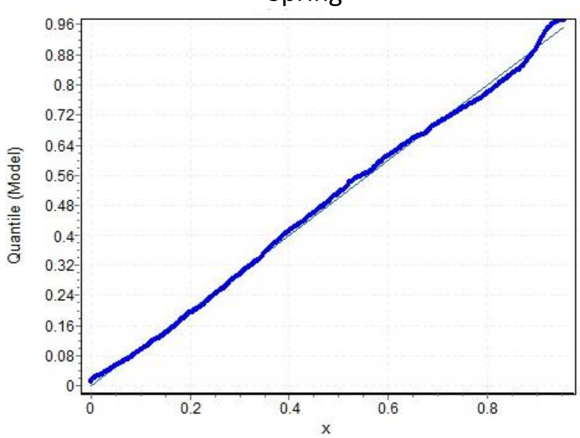
The Q-Q plots for wind models based on Johnson SB PDF are shown below. It is clear that the error between the model and the real data is very small.



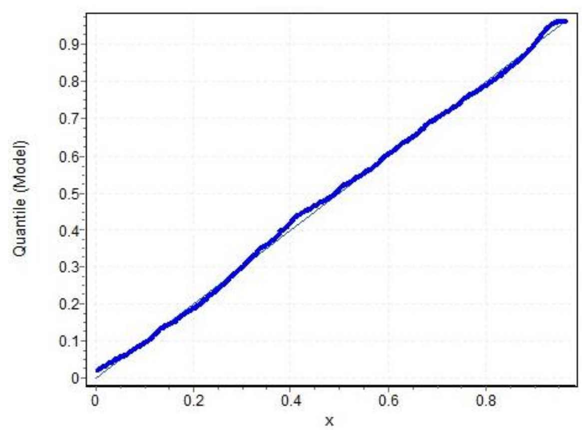
Spring



Summer

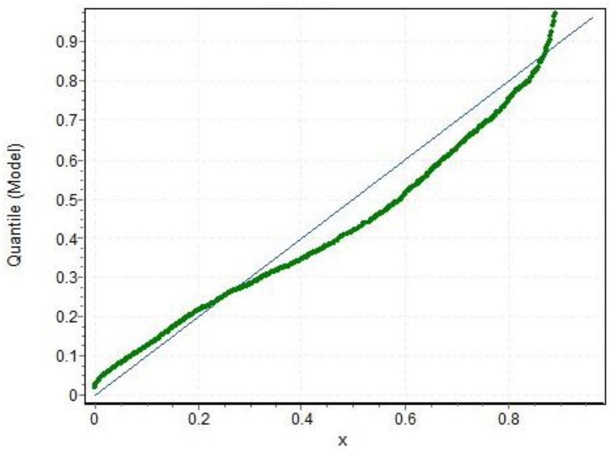


Fall

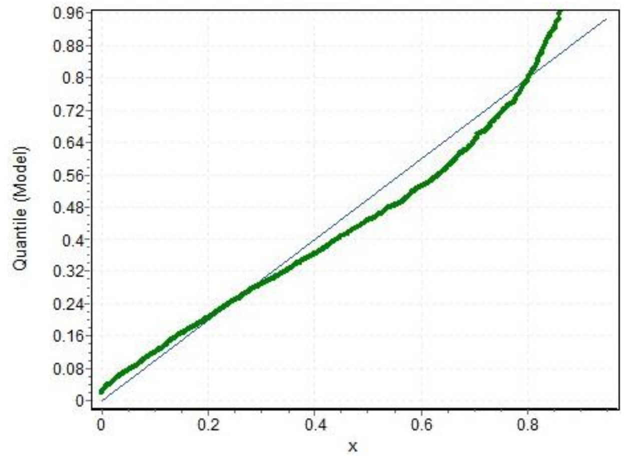


Winter

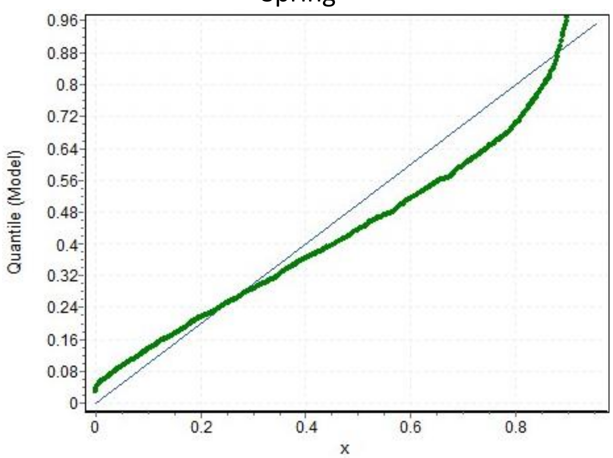
The Q-Q plot when using Weibull to model wind power:



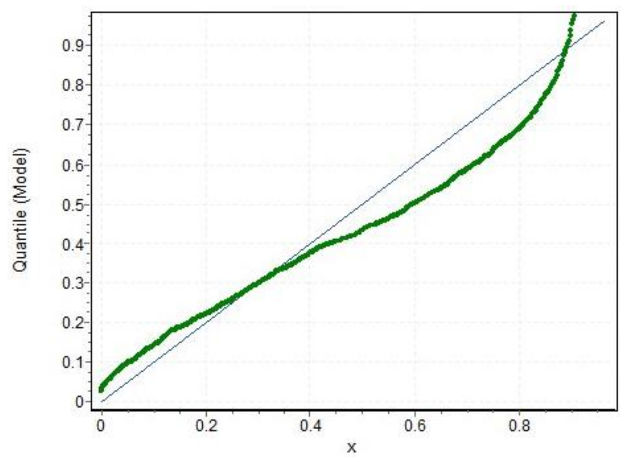
Spring



Summer



Fall



Winter

It is clear from the Q-Q plots for the Weibull model that there is large mismatch between the model and the actual wind data.

Appendix C: Mapping the project format to the energy modelling initiative format

Energy Modelling Initiative (Project Format)	**A Cluster-Based Load Model for a Resilient and Sustainable Community (Project Format)**
6. The Model (10 pages)	2. Model Development: Pages (7-19)
a. Its nature / type of results	2.1 Model nature and cluster development 2.2 Analytical-based model 2.4 Probabilistic-based model
b. Its strengths and limitations	5.3 Model limitations Page (32)
c. How it compares with other models with similar objectives	5.2 Comparisons with other models with similar objectives
d. Its place in the energy landscape / modelling ecosystem	4. Modular Cluster-Based Load Model (Table 16)
e. The state of development & evolution roadmap	5.1 State of development and available models
7. Modelling Results (10 pages)	3. Modelling Results
a. Presentation and interpretation of results	2.3 Type of results in analytical-based model 2.5 Type of results in probabilistic-based model
8. Model's Place in the Ecosystem (10 pages)	
a. Usage (5 pages)	3. Modelling Results
i. Concrete examples	
1. Current and past studies	3.1 Cluster-based probabilistic model 3.2 Cluster-based load profile model
2. Possible future studies	3.3 Dynamic nature of a cluster-based model 3.4 Mathematical dynamic model parameters
ii. How can the model help with policy elaboration?	5.4 Policies and current model 3.5 Indirect parameters of cluster-based load profile
b. Possible synergy with other models (5 pages)	5. Other Models with Similar Objectives Pages (29-30)
i. How can we go beyond current results (what's needed)?	5.2 Comparison with other models with similar objectives Page (30)
ii. Does it make use of common data sets?	4. Modular Cluster-Based Load Model (Page 28)
iii. Is it a standalone tool only?	4. Modular cluster-based load model 5.2 Comparison with other models with similar objectives Page (30) 5.4 Policies and current model Page(32)
iv. If not, has it soft or hard coupling?	
v. Does it feed on other models' outputs?	
vi. Can it produce inputs for others?	