DENSYS

MASTER ERASMUS MUNDUS DECENTRALISED SMART ENERGY SYSTEMS

UNIVERSITÉ DE LORRAINE

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BELIZE ELECTRICITY LIMITED

DEVELOPMENT OF A WEB APP FOR THE OPTIMAL DISPATCH OF ENERGY FROM RENEWABLE SOURCES

By

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ABSTRACT

The electricity sector in Belize is undergoing a transformative shift, characterized by the rapid integration of innovative technologies such as rooftop solar and electric vehicles into the traditional power distribution framework. As the imperative to decarbonize the electricity sector gains prominence, there emerges a compelling need for the electric utility to play a pivotal role in balancing the variable power generation from these devices with demand. This role, executed at a granular level, holds the potential to enhance energy resiliency, minimize delivery losses, and effectively communicate price signals to consumers. Presently, this function relies heavily on manual economic dispatch mechanisms, an inaccurate process, which becomes increasingly challenging given Belize's imminent multitude of variable renewable and small-scale consumers with diverse preferences.

This thesis draws on inspiration from diverse research papers seeking to introduce an innovative paradigm, termed "Decentralized Locational Marginal Pricing" (DLMP), as well as more traditional optimization algorithms like Particle Swarm Optimization (PSO) and Locational Marginal Pricing (LMP). By combining PSO or LMP with DLMP, a price signal at each injection node can be passed to both consumers and utility scale battery management systems to intelligently charge or discharge. Results from the study, indicate that residential BESS will become competitive in the Belizean Market around 2026 with current trends.

This thesis explores the potential of Belize's evolving energy landscape, underpinned by decentralized economic dispatch, to navigate the complexities of integrating renewables, optimizing energy dispatch, and fostering a resilient and sustainable power grid. By harnessing innovative technologies and computational methodologies, Belize can effectively transition to a dynamic energy ecosystem that accommodates both traditional and emerging energy sources, echoing the global imperative for a sustainable and decarbonized electricity sector.

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ABBREVIATIONS

ACE: Area Control Error
UC: Unit Commitment
LF: Load Forecasting
ED: Economic Dispatch
PSO: Particle Swarm Optimization
LMP: Locational marginal Pricing
DLMP: Decentralized Locational Marginal Pricing
BESS: Battery Energy Storage System

GLOSSARY

Ancillary services: are the variety of operations on the electricity networks that are required to balance supply and demand over all time scales, while maintaining voltage and frequency within safe limits and preventing overload of grid infrastructure.
Distributed generation: Term applied to a variety of small power supplies (eg. solar) located near the point where the power is used and tied to Distribution Networks (low voltage). Opposite of central power.
Prosumer: A prosumer is an individual who both consumes and produces.
Utility-scale facility: one which generates solar power and feeds it into the grid, supplying a utility with energy typically above 1 MW and usually feeder to the transmission grid. Utility-scale solar facility typically has a power purchase Agreement (PPA) with a utility, guaranteeing a market for its energy for a fixed term of time.
Residential-scale facility: one which produces energy mostly for self-consumption but may export to the grid. It is usually connected to the distribution grid and remuneration is handled by an aggregator who negotiates with the utility or by a commercial agreement with the utility.
Transmission Grid: the part of the network that wheels wholesale power from IPPs to distribution nodes (distribution substations) at high voltages 115kV, 69kV or 34.5kV.
Distribution Grid: the part of the network that wheels energy from the distribution substation to residential and commercial customer at a lower voltage 22kV, 11kV, 6.6kV.

1.0 INTRODUCTION

1.1 General

Belize, nestled in the heart of the Caribbean, boasts a reputation as one of the region's leading producers of renewable energy. Yet, amidst the natural splendor of this nation, a significant portion of Belize's electricity mix relies on imported power and fossil fuels, predominantly diesel-fired turbines. Despite the strides made in the past years, Belize finds itself at a crossroads, grappling with a dual challenge: economic sustainability and environmental responsibility.

Between 2017 and 2021, an impressive 44% of Belize's power output came from green sources, notably hydro and biomass (bagasse) [1]. Yet, 47% of the electricity was imported, mainly from Mexico's Comisión Federal de Electricidad (CFE), with an additional 9% produced by in-country diesel-powered turbines. The Peninsular Region of the Mexican SIN grid, which supplies Belize, draws merely 12% of its energy from renewables, with the majority dependent on fossil fuels [2]. Depending on these external supplies has significant economic implications, costing Belize around 3.7% of its GDP in foreign exchange for electricity payments. This considerable outflow emphasizes the urgent need for Belize to pursue a more independent and sustainable energy trajectory [1].

Figure 1: Geographical Map of Belize showing Transmission Network and Substations

As highlighted in BEL's 2021 Annual Report, the power cost is a major and unpredictable component of the country's total expenditures. The imperative to tackle this issue is magnified by the aim to stabilize price oscillations and reduce Belize's fossil fuel reliance. Belize understands that strength comes from boosting domestic energy production, particularly through deliberate solar energy investments.

Importantly, Belize's top authorities recognize that an over-dependence on fossil fuel power magnifies the area's environmental impact, contributing to the broader issue of global climate change. To address this, the leaders of all 15 CARICOM nations, Belize included, united to endorse the CARICOM Energy Policy in 2013.

This pivotal pact obligated the region to systematically elevate its green energy capacities. The set milestones were demanding: reach 20% renewable capacity by 2017, 28% by 2022, and a striking 47% by 2027. Remarkably, Belize surpassed expectations, touching the 47% mark as early as 2022.

Taking further initiative, Belize fervently advocates for rooftop solar projects and has proclaimed an even bolder national objective: deriving a minimum of 75% of its energy from green sources by 2030. This vision is consistent with the pledges voiced at the global COP26 summit in Glasgow.

Industry specialist evaluations validate the attainability of this goal, pointing to a balanced blend of hydro, solar, and biomass as the way forward. While hydro presents potential, its scalability has bounds. It's evident that as Belize advances, fulfilling its rising electricity needs and meeting these green energy targets demands a mix of utility and solar Distributed Generation (DG).

Considering these hurdles and prospects, the emergence of a refined technical solution shines brightly. Such an innovation not only matches Belize Electricity Limited's aims but also plays a pivotal role in carving a greener, more resilient energy pathway for Belize. This technological venture is set to transform Belize's energy horizon, harmonizing economic growth with ecological conservation.

1.2 Objectives

In the dynamic landscape of the Belizean energy sector, Belize Electricity Limited (BEL) stands as a central pillar, entrusted with the crucial responsibility of procuring, producing, and delivering electrical energy to the nation. In pursuit of its core mission, BEL has meticulously outlined a set of strategic objectives aimed at optimizing its operations, ensuring energy affordability, and fostering the sustainable development of Belize. This introduction provides a comprehensive overview of BEL's key objectives and underscores the pivotal role of a novel web application, designed to empower BEL in achieving its multifaceted goals.

Least Cost / Least Risk: Foremost among BEL's objectives is the commitment to delivering energy services to Belizeans at the least cost, characterized by minimal price fluctuations. This commitment extends to supporting the quality of life, bolstering the productivity of enterprises, and contributing to national development. Energy Security is paramount, aiming to avert over-dependence on single energy sources, such as wind or solar, while mitigating exposure to spot market dynamics and reducing fuel dependency.

Sustainability: In harmony with the global call for environmental stewardship, BEL's second core objective revolves around sustainable energy production and procurement. It emphasizes the imperative of generating and procuring energy in an environmentally responsible manner, devoid of actions that degrade the natural environment. A crucial metric for sustainability is the percentage of energy requirements covered by renewable sources, with a minimum target of 75% by 2030. Additionally, BEL aims to minimize its carbon footprint, with the ultimate aspiration of Belize achieving carbon neutrality by 2050.

Reliability, Quality of Service, and Resiliency: Ensuring a reliable and resilient energy supply is central to BEL's mission. This objective assesses the system's capacity to efficiently produce, procure, and deliver energy to customers while minimizing interruptions. It seeks to enhance the quality of life, productivity, and the management of high-impact, low-probability events. Metrics for evaluation include system reliability, service quality, and preparedness to withstand and recover from disruptive events.

As BEL embarks on this transformative journey, these objectives collectively form the bedrock of its vision for a sustainable, reliable, and cost-effective energy future for Belize. The development of a sophisticated web application aligns seamlessly with BEL's aspirations, as it equips the company with the tools necessary to navigate the complex energy landscape, optimize its operations, and contribute meaningfully to the well-being and prosperity of Belize and its people.

1.3 Results of Analysis

To be added before November 14

1.4 Recommendations

To be added before November 14

2.0 LITERATURE REVIEW

2.1 Computer Language Comparison Python vs. C#

In the realm of web application development, the choice of programming language plays a pivotal role in shaping the project's trajectory. For this research project, a critical analysis of two prominent languages, Python and C#, was conducted to discern their strengths, weaknesses, and overall suitability in the context of a web application tailored to the specific needs of Belize Electricity Limited (BEL).

Python is a versatile and dynamically typed language known for its readability and ease of use. It offers a plethora of web frameworks, with Django and Flask being notable examples. Python's simplicity accelerates development, making it a preferred choice for rapid prototyping and iterative development. Its expansive standard library simplifies common tasks and facilitates seamless integration of various components.

C#, on the other hand, is a statically typed language developed by Microsoft. It is widely used for building Windows applications, but its capabilities extend well into web development with the ASP.NET framework. C# excels in performance and type safety, making it an ideal choice for projects where speed and reliability are paramount.

To compare Python and C# effectively, this project delved into various aspects, including:

Development Speed: Python's concise syntax and wide array of libraries often result in quicker development cycles. C#, while more verbose, compensates with robust development tools and a strong ecosystem.

Performance: C# is known for its superior performance, making it suitable for resource-intensive applications. Python, while not as performant, boasts extensive optimization tools and can be potent for most web applications.

Ecosystem and Libraries: Python's extensive library support includes Django for full-stack web development and Flask for lightweight applications. C# leverages the ASP.NET ecosystem, which is particularly well-suited for enterprise-level applications.

Community and Support: Python enjoys a massive, global community, fostering vibrant discussions and ample resources. C# benefits from strong Microsoft support and is favored in enterprise environments.

Scalability: Python's scalability depends on the chosen framework and architecture. C#, with its focus on enterprise development, excels in building highly scalable applications.

The research uncovered that Python shines in scenarios requiring rapid development, ease of use, and a wealth of third-party packages. C#, conversely, emerges as a powerhouse for performance-demanding applications, especially in enterprise settings.

In the context of BEL's web application development, the choice between Python and C# hinges on specific project requirements. Python's agility may be advantageous for swiftly prototyping and iterating on solutions, while C#'s robustness and performance could be indispensable for mission-critical applications. This comparative analysis serves as a foundational decision-making tool to ensure that the selected language aligns seamlessly with BEL's objectives and project goals.

2.2 Web Framework Comparison: Django vs. ASP.NET Core

The selection of a web framework is a pivotal decision in the development of web applications, and it greatly influences the project's trajectory. In the context of Belize Electricity Limited (BEL), a comprehensive analysis was undertaken to discern the most suitable framework between Django and ASP.NET Core for the development of a web application tailored to BEL's specific needs.

Django:

- Overview: Django is a high-level Python web framework celebrated for its rapid development capabilities and its "batteries-included" philosophy. It follows the Model-View-Controller (MVC) architectural pattern, emphasizing code reusability and scalability.

- Advantages:

    - Rapid Development: Django's robust set of built-in features, such as an ORM (Object-Relational Mapping) system, admin interface, and authentication, accelerate the development process.
    - Scalability: Django's architecture is designed to handle growth, making it suitable for projects of various sizes.
    - Community and Ecosystem: Django boasts a large, active community and a vast library of third-party packages, enabling developers to extend its functionality easily.
    - Security: Django incorporates security best practices, such as

protection against common vulnerabilities like SQL injection and cross-site scripting (XSS).

ASP.NET Core:

- Overview: ASP.NET Core is a versatile, open-source web framework developed by Microsoft. It operates on the .NET Core runtime, providing cross-platform compatibility.
- Advantages:
    - Performance: ASP.NET Core is renowned for its exceptional performance, particularly in scenarios requiring high concurrency and resource efficiency.
    - Versatility: ASP.NET Core supports a wide range of deployment options, including Windows, Linux, and containerized environments.
    - Integration with Microsoft Stack: For organizations that rely on Microsoft technologies, ASP.NET Core seamlessly integrates with other Microsoft products and services.
    - Security: ASP.NET Core incorporates robust security features and is regularly updated to address emerging threats.

Characteristic	**Django**	**ASP.NET**
Best for Server Side Processing	✓	
Best for developing REST API		✓
Scalability		✓
Ease of Developing Prototype	✓	
Windows Environment Integration		✓
Maturity and Plugins	✓	✓
Speed of Development	✓	

Table 1: Comparison of Web Frameworks

The research revealed that Django excels in scenarios where rapid development and code simplicity are paramount. Its comprehensive feature set and extensive community support make it a top choice for web applications that require agility.

ASP.NET Core, on the other hand, shines in performance-critical environments and within organizations heavily invested in the Microsoft ecosystem. Its scalability, cross-platform compatibility, and integration with Microsoft technologies make it a formidable choice for enterprise-level projects.

The choice between Django and ASP.NET Core for BEL's web application development depends on specific project requirements and organizational preferences. Django offers speed and ease of use, while ASP.NET Core delivers unparalleled performance and Microsoft integration. This comparative analysis serves as a valuable guide to ensure that the selected framework aligns seamlessly with BEL's objectives and project goals.

2.3 Deep Neural Network Models

TensorFlow is an open-source machine learning framework developed by the Google Brain Team. It was designed with the aim of providing a flexible, scalable, and production-ready platform for developing a wide range of machine learning models, from simple linear regressions to complex deep neural networks (DNNs). One of the most compelling features of TensorFlow is its computational graph abstraction. Instead of running operations step-by-step, TensorFlow defines a computational graph where nodes represent mathematical operations, and the edges represent multidimensional arrays (tensors) passed between them. This allows for efficient and optimized parallel computations, especially on GPU hardware.

TensorFlow's adaptability stems from its modular design. Its high-level APIs, like Keras, simplify the process of model design, making it accessible even to those new to machine learning. For more intricate designs or research purposes, TensorFlow provides low-level APIs to offer granular control over model architectures and training loops.

Deep Neural Networks (DNNs) are a class of machine learning models that have gained significant attention in recent years due to their unprecedented successes in tasks like image recognition, natural language processing, and predictive analytics. DNNs consist of multiple layers of interconnected nodes (neurons) that transform the input data into a desired output. The 'deep' in DNNs refers to the depth of these layers, which can number from tens to hundreds in advanced architectures.

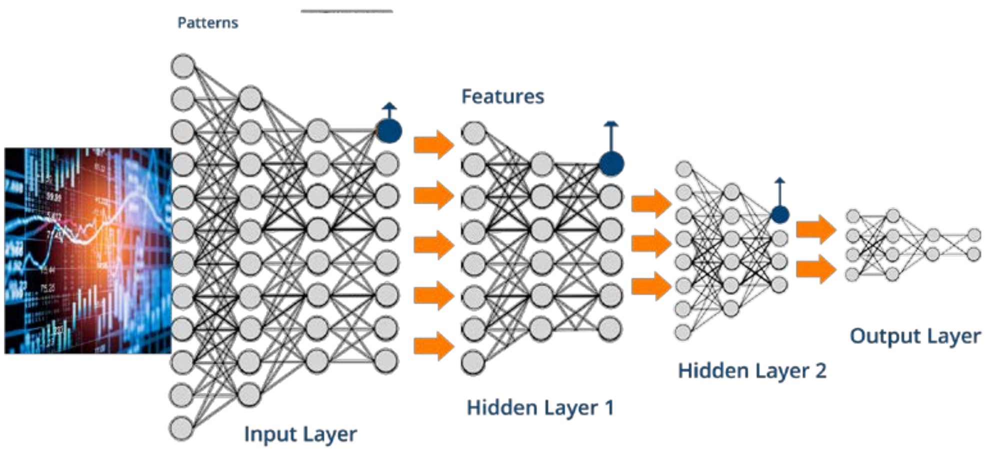

Figure 2: Representation of perceptrons in Deep Neural Network

A DNN learns by adjusting the weights of its connections based on the error between its predicted output and the actual output during training. This process is often guided by backpropagation, a technique that calculates the gradient of the error with respect to the model's weights. The weights are then updated using optimization algorithms like Stochastic Gradient Descent (SGD) or its variants.

Several factors contribute to the effectiveness of DNNs. With a sufficient number of neurons and layers, DNNs can approximate any continuous function, given the right set of weights. In tasks like image recognition, initial layers might capture simple patterns (e.g., edges or textures), while deeper layers combine these to detect complex structures (e.g., shapes or objects).

In the context of the project, a feedforward neural network was employed to predict the P and Q load values based on a set of features derived from combined feeder and weather station data. The neural network architecture consists of two hidden layers with 64 and 32 neurons, respectively, and an output layer designed to predict both P and Q values.

The chosen model was compiled with the Adam optimizer, which is an adaptive learning rate optimization algorithm designed to handle sparse gradients on noisy problems. The mean squared error was used as the loss function, which is appropriate for regression tasks where the goal is to minimize the difference between predicted and actual values.

Training a neural network model involves iteratively updating its weights using the provided training data until the model's predictions closely match the observed outcomes. In this project, the model was trained over 100 epochs with a batch size of 32. After training, the model was serialized and stored for later use, allowing the web app to make predictions on new data quickly and efficiently.

In conclusion, TensorFlow and deep neural networks provide a robust and flexible framework for developing predictive models for diverse applications. Their ability to learn intricate patterns from large datasets makes them especially suited for tasks like load forecasting and generation forecasting.

2.4 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a metaheuristic optimization technique inspired by the social behaviors exhibited by flocking birds or schooling fish. The algorithm represents potential solutions as individual particles within a swarm, and these particles move through the solution space based on their own experience and the experience of their neighbors. According to Barnika Saha and Suraj Rath, the algorithm leads to reliable and stable convergence for a 30-bus electric network [3].

In PSO, each particle has a position in the search space, representing a potential solution to the problem at hand. Along with its position, each particle has a velocity determining its direction and distance of movement in the next iteration. As the particles "fly" through the solution space, they remember their best position (p_{best}) and also have knowledge of the best position among all particles (g_{best}). The movement of each particle towards the p_{best} and g_{best} positions in the search space is influenced by random factors, which ensures exploration and exploitation of the search space.

The update equations for the position and velocity of each particle are as follows:

$$v_i^{(t+1)} = \mathrm{w} \times v_i^{(t)} + \mathrm{c1} \times rand \times \left(p_{best,i} - position_i^{(t)}\right) + \mathrm{c2} \times rand \times \left(g_{best} - position_i^{(t)}\right)$$

$$\mathrm{position}_i^{(t+1)} = \mathrm{position}_i^{(t)} + v_i^{(t+1)}$$

Where:

$$v_i^{(t)} = \text{velocity of particle i at time t}$$

$$\text{position}_i^{(t)} = \text{position of particle i at time t}$$
$$p_{best,i} = \text{best known position of particle i}$$
$$g_{best} = \text{best known position among all particles}$$
$$\text{w} = \text{inertia weight}$$
$$\text{c1, c2} = \text{acceleration coefficients}$$
$$\text{rand} = \text{random number between 0 and 1}$$

The challenge in optimizing power generation across various nodes lies in the multidimensional nature of the problem. Each node has different power generation capabilities, constraints, and requirements. By utilizing PSO, we can efficiently navigate this vast solution space to identify optimal power outputs for each node.

In the context of this project:

1. Each particle represents a specific configuration of power generation across the nodes.

2. The fitness or objective function is to minimize the cost of overall power generation plus valorized transmission losses while ensuring individual node constraints are met.

3. Based on the fitness values, the p_{best} and best valuess are updated. Particles then adjust their velocities and positions according to the PSO equations, moving towards the more optimal areas of the solution space.

4. The algorithm continues until a stopping criterion is met, such as a maximum number of iterations or when the solution quality reaches an acceptable threshold.

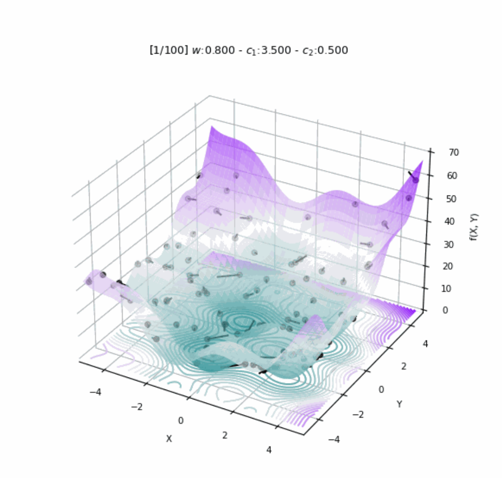

Figure 3: Graph of particles on the search domain converging on the global minimum

By applying Particle Swarm Optimization to the problem of power generation optimization at nodes, we can explore a wide variety of power distribution configurations efficiently. This ensures that we find a solution that maximizes power generation and distribution while adhering to the constraints and requirements of each node. PSO's ability to balance between exploration and exploitation makes it an ideal choice for such complex, multi-dimensional problems.

2.5 Locational Marginal Pricing

In their paper, Authors Haifeng Liu, Leigh Tesfatsion, and A. A. Chowdhury, who are associated with IEEE, discuss the basics of Locational Marginal Pricing (LMP) in the context of restructured wholesale power markets. It delves into the concepts, definitions, calculations, and related constraints associated with LMP. Although, LMP is primarily utilized in a deregulated power market with variable pricing and Belize currently has a fixed price scheme, the LMP provides invaluable pricing data that is necessary to optimize the battery charge and discharge cycles of both utility and residential BESS.

Locational Marginal Pricing (LMP) signifies the cost associated with delivering an incremental unit of electricity to a specific point in the electricity grid. In the context of this study, LMP ensures that the dispatch of electricity is performed in the most economically efficient manner.

LMP consists of three primary components. The first is energy cost which represents the incremental cost of electricity generation. Next is congestion cost which corresponds to the price implications of transmission bottlenecks, which can prevent the most economical power sources from supplying electricity to all regions. The last is loss cost which quantifies the costs associated with energy losses during the transmission process.

The goal is to employ LMP in BEL's daily operations by using advanced optimization algorithms. These algorithms factor in technical grid constraints, variable generation costs and limits, and the intricacies of transmission.

LMP values differ across grid locations due to variations in transmission constraints and inherent power losses. These values will guide dispatchers in deciding which generation units should be dispatched and their respective outputs to most economically meet the demand.

When applied to optimization problems, LMP helps ascertain the most economical dispatch of generation assets. The decision variables and constraints in this optimization context are detailed below:

The AC OPF problem aims to minimize the total generation cost while meeting system demand and ensuring all technical constraints are satisfied. The primary equations are:

Objective Function (Cost Minimization):

$$\min_{p_i, q_i, x} \sum_{i \in \mathrm{I}} c_i(p_i)$$

Where:

$c_i(P_{Gi})$ = cost function of the generator (i) as a function of its real power output (P_{Gi}).

Power Balance Constraints:

Real Power:

$$f_{pk}(x) + \xi_k + D_k - \sum_{i \in \mathrm{I}_k} p_i = 0 \quad \text{for} \quad k = 1, \dots, N$$

Reactive Power:

$$f_{qk}(x) + Q_{\text{load}_k} - \sum_{i \in \mathrm{I}_k} q_i = 0 \quad \text{for} \quad k = 1, \ldots, N$$

Where:

$x = [\theta_1\ \theta_2 \cdots \theta_{N-1}\ \mathrm{V}_1\ \mathrm{V}_2 \cdots \mathrm{V}_{N-1}]$

$f_{pk}(x)$ is the real power flowing out of bus k:

$$f_{pk}(x) = \sum_{i=1}^{N} V_k V_i [G_{ki} \cos(\theta_{ki}) + B_{ki} \sin(\theta_{ki})]$$

$\mathrm{f}_{\mathrm{qk}}(\mathrm{x})$ is the reactive power flowing out of bus k:

$$\mathrm{f}_{\mathrm{qk}}(\mathrm{x}) = \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{V}_{\mathrm{k}} \mathrm{V}_{\mathrm{i}} [\mathrm{G}_{\mathrm{ki}} \sin(\theta_{ki}) - \mathrm{B}_{\mathrm{ki}} \cos(\theta_{ki})]$$

I_k is the set of generators connected to bus k

p_i is the real power output of generator i

q_i is the reactive power output of generator i

D_k is the given real power load at bus k

Q_{load_k} is the given reactive power load at bus k

ξ_k is an auxiliary parameter associated with bus k that is set to zero. Changes in ξ_k will later be used to parameterize the real load increase at bus k in order to derive the real power LMP at bus k.

V_k and V_i are the voltage magnitudes at nodes k and i, respectively.

$\theta_{ki} = \theta_k - \theta_i$ is the voltage angle difference between nodes k and i

G_{ki} and B_{ki} are the real and imaginary parts of the admittance between nodes k and i.

Network Constraints:

$$0 \leq S_{ij}(x) \leq S_{ij}^{max}$$
$$V_k^{min} \leq V_k \leq V_k^{max}$$

Where:

$S_{ij}(x)$ is the magnitude of the complex power flowing from bus i to bus j

V_k^{min} and $V_k^{max}$are the minimum and maximum Voltage Magnitudes bus k

Generator Output Constraints:

$$p_i^{min} \leq p_i \leq p_i^{max}$$
$$q_i^{min} \leq q_i \leq q_i^{max}$$

Where:

p_i^{min} and p_i^{max} are the minimum and maximum real power outputs for generator i, respectively.

q_i^{min} and q_i^{max} are the minimum and maximum reactive power outputs for generator i, respectively.

The AC OPF model provides higher accuracy compared to the DC OPF model, though it often faces convergence issues. Furthermore, the AC OPF can take up to 60 times longer than its DC counterpart [4]. For calculating LMP in power market operations, the DC OPF model (sometimes referred to as the linearized AC OPF model) is commonly utilized. LMPs are calculated using the DC Optimal Power Flow (DC OPF) model. However, there are certain assumptions and simplifications in the DC OPF model that one must be aware of, especially in the context of LMP calculations.

The DC OPF model linearizes the power flow equations, making the computational process simpler and faster. This is particularly useful for real-time and day-ahead market operations.

While the DC OPF model provides a simplified approach to calculating LMPs, it's important for power system operators and market participants to be aware of its limitations. When the aforementioned conditions are not met, the DC OPF may lead to inaccuracies in LMP values. In such cases, using an AC OPF model or applying corrective factors might be necessary to get more accurate pricing signals.

The Power Balance Constraints of the AC OPF problem become reduced to:

$$\sum_{m=1, m\neq k}^{N} \left[\frac{1}{X_{km}}(\theta_k - \theta_m)\right] = \sum_{i \in I_k} P_i - D_k = P_k - D_k \quad \text{for } k = 1 \dots N$$

Where:

X_{km} is the Reactance of the line from bus k to m

θ_k *and* θ_m are the voltage angles at bus k and m

This is only acceptable under these assumptions:

- Voltage Angles Difference are very small and so the sine and cosine of the angle difference can be approximated as:

  $$\cos(\theta_k - \theta_m) \approx 1$$
  $$\sin(\theta_k - \theta_m) \approx \theta_k - \theta_m$$
- DC OPF assumes a lossless transmission system. This is equivalent to having very low branch power. This allows us to assume the voltage profile across the network should be relatively flat. Typically, the bus voltage is assumed to be 1 per unit.

- The DC OPF model becomes more accurate when the resistance to reactance ratio (R_{km}/X_{km}) of the transmission lines is less than 0.25. Systems with higher rkm/xkm ratios may exhibit discrepancies between the DC and AC OPF results.

2.6 Decentralized Locational Marginal Pricing

The DLMP algorithm proposed by Sruthi Davuluri at MIT integrates perfectly with Belize's radial electric distribution systems [5]. This approach is designed to tackle the central problem of maintaining system stability in a small grid like Belize's network while trying to profitably accommodate the uptake of renewable energy by catering to prosumers individualized demand functions. Computational feasibility and adherence to the physical constraints of the system are also addressed in this approach. Unlike existing methodologies, which often involve numerous iterations or lack convergence, the algorithm presented here consistently converges to the same solution as a centralized operator armed with perfect information, and it achieves this convergence with only two system-wide sweeps [5]. Through a proofof-concept analysis conducted on a 46-bus system, this research demonstrates the tangible physical and economic advantages of the decentralized algorithm, even when managing varying levels of distributed energy resources.

DLMP solves the limitations of centralized OPF algorithms like PSO and LMP. OPF assumes perfect information under static scenarios. It is not feasible for centralized operators like BEL to account for many distributed resources at the household level. The increased penetration of Distributed Energy Resources (DER) exacerbates information asymmetry. Renewable energy resources, which are intermittent and harder to predict, strain the traditional model. Lastly, current models do not adequately factor in diverse customer preferences or the varied elasticity of demand for different products.

The decentralization of optimization calculations overcomes the challenges of information asymmetry and diverse demand functions. This is achieved by the implementation of more localized operations, e.g., solving the objection function at each prosumer node. There are technologies that enable this such as smart meters which host Linux operating systems. Manufacturers provide SDKs for creating customized apps.

DLMP relies on a recursive distributed algorithm where downstream nodes communicate with upstream parent nodes. The radial distribution network is modeled as a graph. Nodes in this graph have relationships (parent-child), which denote informational or physical connections. Since all distribution feeders in the BEL network are radial, the algorithm can leverage BEL GIS data to establish connectivity.

True, real-time optimization can be achieved with a decentralized operation, where data processing and decision-making are distributed across multiple nodes or entities as opposed to the traditional centralized approach. With decentralization, each node or entity might make decisions based on localized information, which could be more detailed and timelier than information available in a centralized system.

In order to qualify as an agent, a prosumer must be able to control the energy exported and imported into the grid such as by utilizing BESS. As each agent will function as a dispatchable generator, it must determine how much to feed or take from the grid. This can be achieved by two sweeps across the graph. The forward sweep starts at nodes at the periphery and ends at the head node which is at the substation. The head node receives pricing information for energy from the transmission grid at that node.

The forward sweep optimization function is:

$$\prod i, Forward: \min_{x_i, y_{ic}} C_i(x_i) + \sum_{c \in \mathbb{C}_i} B_c(y_{ic})$$

$$s.t.: \; x_i + \hat{y}_{pi} = \sum_{c \in \mathbb{C}_i} y_{ic} \quad (\lambda_i)$$

$$x_i^{min} \leq x_i \leq x_i^{max}$$

$$F_{ic}^{min} \leq y_i \leq F_{pi}^{max}$$

Where:

$\hat{y}_{pi}$ is the parent branch injection

y_{ic} is the child branch injection from child c to node i
x_i is the power injected at the node by agent i
C_i is the cost function of agent i
B_c is the children bid function
F_{ic}^{min} and F_{pi}^{max} are the branch power limits
λ_i represents the solution of the Lagrangian for three different expected injections from the parent nodes $(\lambda_i, \hat{y}_{pi})$, $(\lambda_i^+, (1+\epsilon)\hat{y}_{pi})$, $(\lambda_i^-, (1-\epsilon)\hat{y}_{pi})$ where ϵ is chosen to be a small number such as 0.001

The backward sweep optimization function is:

$$\prod i, Backward: \min_{x_i, y_{pi}, y_{ic}} C_i(x_i) + \sum_{x \in \mathbb{C}_i} B_c(y_{ic}) + \lambda_{pi} y_{pi}$$

$$s.t.: \ x_i + y_{pi} - \sum_{x \in \mathbb{C}_i} y_{ic} = 0$$

$$y_{pi}^{\min} \leq y_{pi} \leq y_{pi}^{\max}$$

$$x_i^{min} \leq x_i \leq x_i^{max}$$

$$F_{pi}^{min} \leq DF_{ii} x_i + DF_{ip} x_p \leq F_{pi}^{max}$$

Where:

$\hat{y}_{pi}$ is the parent branch injection
y_{ic} is the child branch injection from child c to node i
x_i is the power injected at the node by agent i
DF_{ij} correspond to the element in i^{th} row and j^{th} column of the Distribution Factor matrix DF
λ_{pi} is the Lagrangian solution or the nodal price communicated from the parent node to its children node
B_c is the children bid function
F_{ic}^{min} and F_{pi}^{max} are the branch power limits

The results of DLMP and a centralized OPF were established for the island of Flores in the Azores. DLMP provides a cost similar to OPF for a 46 bus network [5]. In the context of this study, DLMP ensures convergence to an optimal solution comparable to the centralized OPF with perfect information.

2.7 Limitation of Study

Demand is not price sensitive.

3.0 METHODOLOGY

3.1 Framework Selection

In the rapidly changing landscape of web development, companies must make strategic choices that align with their long-term vision and available resources. For our company, the decision to choose ASP.NET and C# over Python and Django is rooted in several crucial considerations. Our company has a significant investment in Microsoft technologies and infrastructure. Adopting ASP.NET and C# ensures seamless integration with our existing systems, thereby reducing the complexities and potential pitfalls of integrating disparate technologies. Django inability to integrate with Microsoft SQL Server is its death knell.

3.2 Weather Data Sources

Accurate weather data is essential for this application. For our project, we sourced weather data from several renowned platforms, evaluating them for the best quality and reliability; namely, meteomatics.com, Tomorrow.io, and Visual Crossing.

For obtaining historical weather data, we relied on the Belize National Meteorological Service. Their data repository, accessible at https://surface.nms.gov.bz/api/rawdata, provided us with an expansive archive of historical weather data. To ensure the highest relevance and accuracy, the weather station closest to each feeder's centroid was selected as the primary data source.

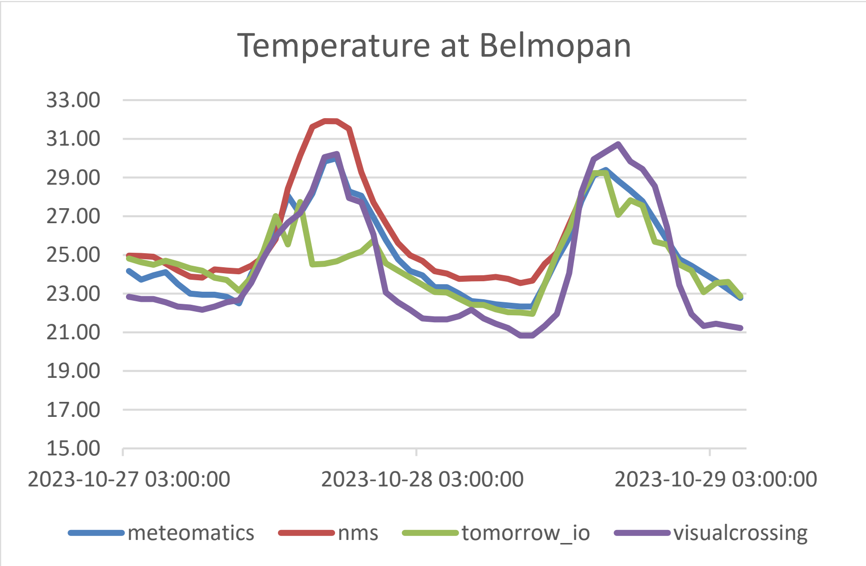

Figure 4: Temperature forecast and historical (nms) for Belmopan Weather Station Location

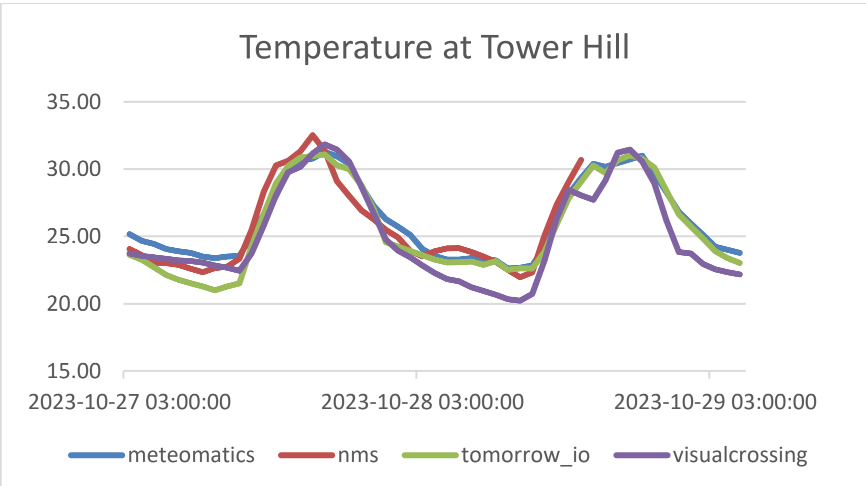

Figure 5: Temperature forecast and historical (nms) for Tower Hill Weather Station

Error - Root Mean Squared Deviation						
Parameter	temperature	humidity	wind_speed	wind_direction	irradiance	rainfall
meteomatics	1.64	14.01	3.42	172.53	99.28	1.93
tomorrow.io	1.59	15.64	3.76	177.12	0.00	2.76
visualcrossings	1.88	15.13	4.25	167.09	154.96	2.03

Table 2: RMSD for weather parameters from three evaluated sources. Tomorrow.io irradiance was not available in trial.

For weather forecasting, we evaluated the three major online platforms. After rigorous testing, both Meteomatics and Tomorrow.io consistently displayed the smallest root mean deviation squared for weather parameters, emerging as top contenders for our forecasting needs.

While both platforms displayed remarkable accuracy, the decision to opt for Tomorrow.io was influenced by its unique feature of supporting polygon shapes in its API. This capability allowed us to obtain average weather parameters across a specified area, providing a more holistic and accurate perspective, especially beneficial for regional analyses.

3.3 Historical Load Data Sources

One of the foundational data sources for our project was the Supervisory Control and Data Acquisition (SCADA) system from Belize Electricity Limited (BEL). The SCADA system, serving as BEL's master data repository, played a pivotal role in offering real-time and historical electrical data essential for our research and operational needs.

From the SCADA master, we primarily extracted two crucial electrical parameters, Active Power (P) and Reactive Power (Q). These parameters are fundamental in understanding and analyzing the power dynamics and the overall performance of the electrical system. To provide a comprehensive analysis, it was imperative to correlate the electrical data with weather patterns. The key to achieving this seamless integration was the use of Coordinated Universal Time (UTC). Both the electrical data from BEL's SCADA and the weather data were timestamped in UTC, ensuring uniformity and precision.

By synchronizing the datasets using UTC time, we were able to superimpose electrical patterns over weather trends, facilitating a holistic understanding of how weather variations influence power dynamics. This synchronization not only improved the accuracy of our analyses but also enriched the depth of insights drawn from the combined data.

3.4 Network Data Source

The foundation of our network analysis and subsequent optimizations was rooted in the comprehensive data extracted from an existing ETAP (Electrical Transient Analyzer Program) model. ETAP, being a robust electrical engineering software, facilitated the precise modeling of our electrical system.

The ETAP model was made available to us in an XML (Extensible Markup Language) format. XML, being a structured document standard, allowed for systematic parsing of the myriad of electrical parameters embedded within. Through a series of parsing algorithms, we were able to successfully extract and interpret all the essential network constraints.

A salient feature of our system is its configurability. Post extraction, the data was seamlessly integrated into our software, enabling users to make real-time modifications. Particularly, users possess the capability to alter the status of switches, thereby actively reconfiguring the network layout. This flexibility empowers users to simulate various operational scenarios and deduce optimal strategies.

The ETAP model was not just limited to basic network layout. It provided in-depth data about generators, including their minimum and maximum active (P) and reactive (Q) power limits. Furthermore, the model outlined specific constraints like line current limits and transformer power limits, crucial for ensuring network safety and efficiency.

Figure 6: Detailed BEL Networks

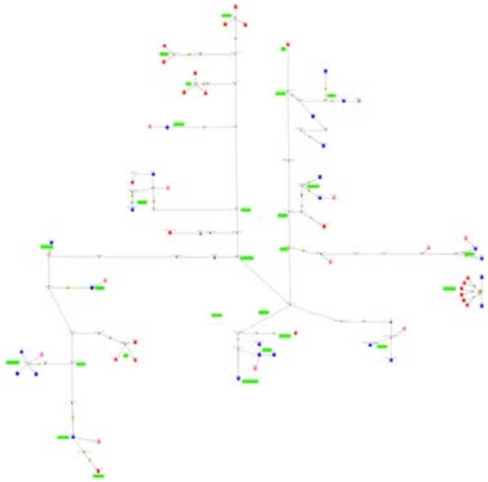

Figure 7: Minimized BEL Networks

In line with our objective of achieving efficient calculations, our software incorporates a network minimization feature. This process involves the removal of unnecessary nodes and edges, simplifying the network without compromising its integrity. The image on the right showcases the streamlined graph post-minimization. This pared-down representation ensures quicker calculations, enhancing the overall user experience.

Through meticulous parsing and integration of the ETAP XML model, we have established a dynamic and configurable network system. The inclusion of in-depth generator data and constraint details, combined with the minimization feature, ensures that our software achieves its goal of efficiency and precision.

3.5 Prediction Model

The construction of our predictive model started with integrating vital weather parameters. Weather plays an indispensable role in power demand fluctuations, especially in Belize where a large portion of load is due to motors in cooling devices like A/Cs and fridges. These formed the bases of our feature inputs while P and Q are the outputs to predict.

To enhance the accuracy and reliability of our predictions, a list of additional elements was integrated into the model. These include:

hour: Recognizing the time of day is vital as power demands vary between peak and off-peak hours.
Week number: Week of the year can indicate demand patterns, especially in touristic regions where there is seasonal demand.
P(1hr ago) and Q(1hr ago): Demand data from an hour ago can provide short-term trend insights.
P(1 day ago) and Q(1 day ago): Daily demand variations can offer a broader view of the demand curve.
Event number: This caters to specific events that may surge or plummet the power demand such as holidays.

P_{avg}(past 3hrs) and Q_{avg}(past 3hrs): Three-hour average values to observe intra-day demand changes.
P_{avg}(past 24hrs) and Q_{avg}(past 24hrs): A day's average to track daily patterns.
Outage energy: One of the most innovative aspects of our model is the inclusion of outage energy, extracted from an outage database. This data represents the unserved energy during outages and will be instrumental in accounting for planned outages in future predictions.

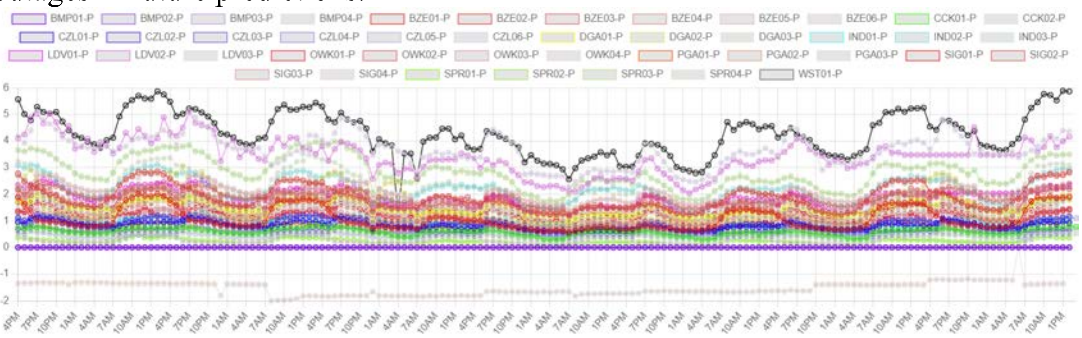

Figure 8: Real Power Demand for a 1 week span for all 44 Feeders

The first image presents a comprehensive view of feeder demands over a week. It demonstrates that despite the natural variability, there exists a significant degree of predictability in demand. Daily rhythms and recurring patterns are evident, showcasing the viability of our predictive approach.

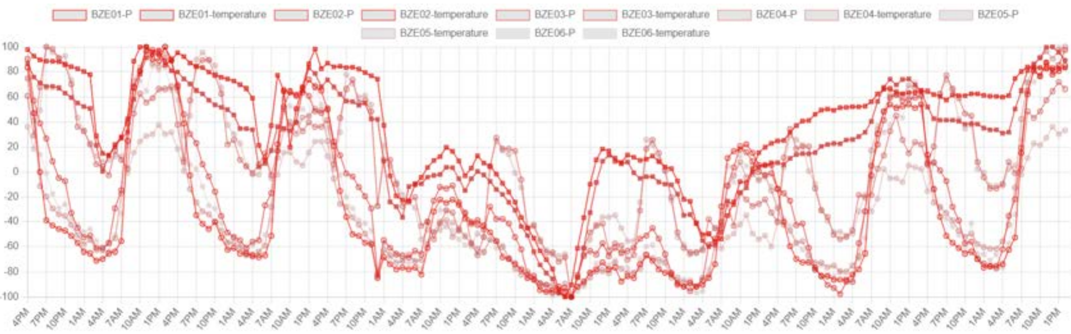

Figure 9: Normalized Real Power, P, and Temperature for 6 Feeders in Belize City (Temperature in Squares)

Figure 10: Normalized Real Power Demand and Humidity for 6 Belize City Feeders

The second image presents a comparison between normalized temperature values and power demand (P). The remarkable correlation between these two variables is evident. As temperature rises or falls, corresponding peaks and troughs in the power demand can be observed. This strong interdependency reinforces the need to consider temperature as a crucial predictor in our model. The third image shows the correlation between P and humidity. Although not as strong as temperature, it is a factor to be inputted into the model.

Our predictive model's construction, rooted in a synthesis of historical data, real-time inputs, and innovative parameters like outage energy, positions it as a robust tool for future demand forecasting. The evident correlation between temperature, humidity and power demand further validates our approach. Such comprehensive modeling ensures grid stability, efficient resource allocation, and optimal power distribution to meet future challenges.

3.6 Generator Costs

For optimal operation and planning of power systems, understanding the efficiency curves of generators is paramount. These curves define how much fuel a generator consumes to produce a given amount of power. As such, they are a critical component for economic dispatch and optimizing operational costs.

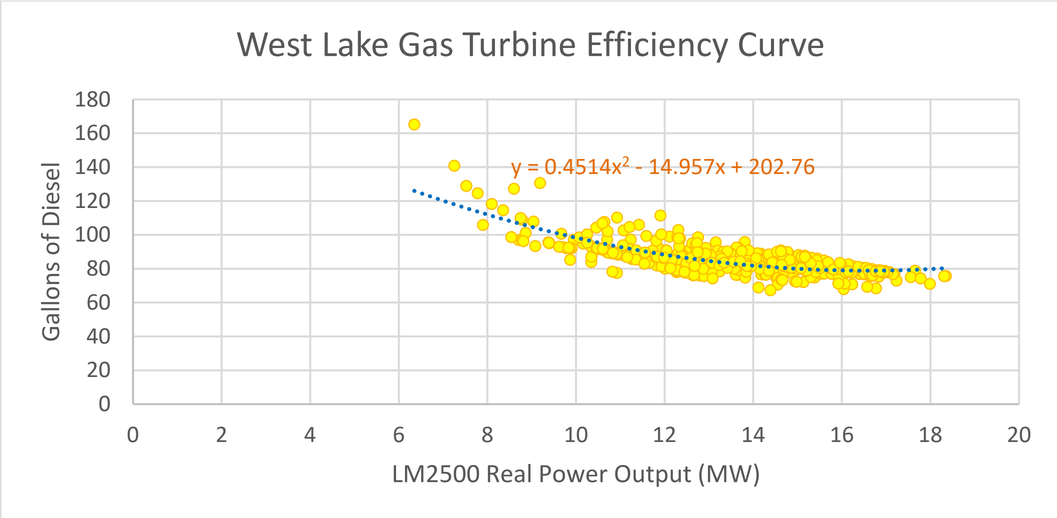

Figure 11: Fuel Consumption of Gas Turbine for Various Operating Points

The efficiency curve for the West Lake Gas Turbine, as showcased in the provided graph, was derived from historical production data. This data comprises records of the power output of the turbine and the corresponding fuel consumption, measured in gallons of diesel. The same methodology was employed with BEL's other generators where the fuel consumption is passed on to consumers.

The data points on the graph represent individual recorded instances of power output and fuel consumption. To extract a tangible relationship from these points, a best-fit curve was employed. The y value is the gallons of diesel consumed and x is the MW output of the generator.

It's evident from the equation and the graph that the relationship between power output and fuel consumption is quadratic, typical for many turbine efficiency curves. The quadratic nature suggests that there are optimal operating points where the turbine is most efficient and deviations from these points result in increased fuel consumption per unit of power output.

The derived fuel efficiency curve is instrumental in optimization problems. With the knowledge of how much fuel is consumed for a given power output, decision-making algorithms can make informed choices about how to dispatch the generator.

For instance, if there's a need to minimize fuel costs during operation, the algorithm can refer to this curve to determine the most fuel-efficient power output level.

Additionally, in a scenario with multiple generators, each with its efficiency curve, the system can be optimized to dispatch the right combination of generators to meet demand at the lowest possible fuel cost.

3.7 Price Forecast

Electricity importation is very important in BEL's strategy to ensure reliability, diversify the energy mix, and capitalize on economical pricing. In the context discussed here, the importation of electricity from Mexico constitutes a significant portion, approximately 40%, of the annual consumption.

Mexico operates a deregulated electricity market, which means that the prices of electricity are determined based on supply and demand dynamics rather than being set by a centralized authority. Within this market, the concept of Locational Marginal Pricing (LMP) is utilized. LMP represents the price of electricity at specific nodes or locations within the grid. It takes into account factors such as generation costs, transmission constraints, and demand at that specific location.

BEL imports electricity specifically from the BEL-115 node in Mexico. Due to the deregulated nature of the market, it's crucial for BEL to have an understanding of the expected price fluctuations at this node to make informed buying decisions.

To aid in decision-making, the Mexican electricity market provides a price forecast for each node. For the BEL-115 node, this forecast is given per hour and extends two days into the future. This granular and short-term forecast allows for more accurate planning, especially when integrating these prices into an optimization problem.

When optimizing the dispatch of generation units and determining the ideal level of electricity imports, the LMP values from the BEL-115 node become a key input. The optimization problem, in this case, is solved as a time series, considering each hour within the two-day forecast period.

The objective of the optimization is to minimize costs, possibly reduce emissions, and ensure good operating reserve margins. Given the significant proportion of electricity that is imported from Mexico, the forecasted LMP values can have a substantial impact on the resulting optimal solution.

For instance, if the LMP values indicate high prices for certain hours, the optimization problem might favor increased local generation (if feasible) during those hours to offset expensive imports. Conversely, during hours when the LMP values are low, it might be more economical to increase imports and reduce local generation.

3.8 Fuel Management

Belize's energy sector features a mix of resources, with hydroelectric dams playing a pivotal role in ensuring a consistent power supply. The Vaca, Mollejon, and Chalillo watersheds feed the three primary dams that fuel a significant portion of the country's energy needs. In an environment where diverse energy sources contribute to the national grid, it's crucial to manage each fuel type effectively. This includes not only traditional fuels like Heavy Fuel Oil (HFO) and diesel but also 'water fuel' – the inflow to the hydroelectric dams.

Figure 12: Water Shed of the three dams where rainfall prediction drive fuel management.

Short-term predictions can be achieved by leveraging meteorological data and river flow rates. It's possible to anticipate inflows for upcoming days and weeks. These predictions guide immediate operational decisions, such as reservoir releases and turbine dispatches.

Long-term predictions are a little trickier. Seasonal weather patterns, historical data, and advanced hydrological models help forecast inflows over months or even years. This assists in long-term planning and infrastructure decisions.

Ensuring that the reservoirs maintain optimum water levels is key to providing a consistent power supply. This requires a delicate balance - holding enough reserve to handle peak demands, yet also allowing for controlled releases to sustain river ecosystems downstream.

While hydroelectric power can provide a consistent energy source, other contributors like biomass are seasonal. During periods when biomass or other sources are at low generating capacity, the dams need to be primed to take on a larger share of the load. Predicting and preparing for these shifts ensures that Belize's energy supply remains stable year-round.

While water is a renewable and sustainable fuel source, Belize's energy grid also relies on traditional fuels, namely HFO and diesel. Effective management of these fuels is essential for several reasons. Ensuring a consistent supply of HFO and diesel requires coordination with suppliers, transportation logistics, and storage considerations. Global oil prices can be volatile. By maintaining strategic reserves and employing hedging strategies, it's possible to mitigate the impact of sudden price hikes. Lastly, traditional fuels have a larger carbon footprint than renewable sources. Effective management also means optimizing their use to minimize environmental impacts.

3.9 Batteries in the Mix

Renewable energy sources, such as solar and wind, have transformed the energy landscape by providing cleaner alternatives to fossil fuels. However, they also introduce a level of variability and unpredictability due to their reliance on natural phenomena. Solar panels, for example, produce energy only during the day and can be affected by cloud cover, while wind turbines rely on wind speeds that can be inconsistent.

To address this variability, batteries can be employed to act as a buffer, storing excess energy produced during peak renewable generation times and releasing it during periods of low generation or high demand. This ensures a consistent and reliable power supply. Rapid fluctuations in renewable generation can lead to voltage and frequency instabilities in the power grid. Batteries can quickly absorb or release energy to stabilize these parameters, ensuring grid reliability. Batteries can also be discharged during periods of peak demand, reducing the need for expensive peaker plants and alleviating stress on the grid.

As the energy sector evolves with more distributed energy resources, there's a growing need for a more granular pricing mechanism – enter nodal pricing. Nodal, or locational marginal pricing (LMP), reflects the value of electricity at specific locations, or nodes, within the grid, considering generation costs, demand, and transmission constraints.

For battery storage systems, nodal pricing plays a crucial role in several ways. Knowing the LMP at different locations helps determine the most economically viable sites to place battery storage systems. Areas with frequent congestion or high price differentials can benefit the most from battery installations. Batteries can be programmed to charge during periods of low LMP (excess supply or low demand) and discharge during high LMP periods, maximizing economic returns. Regions with high LMP variability might signal a higher potential return on investment for battery storage, attracting more developers and investors to those areas.

4.0 RESULTS AND DISCUSSION

4.1 Load Forecast

To be added before November 14

4.2 Problem Constraints

To be added before November 14

4.3 PSO

To be added before November 14

4.4 LMP

To be added before November 14

4.5 DLMP

To be added before November 14

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

To be added before November 14

5.2 Recommendations

To be added before November 14

5.3 Areas for Further Study

To be added before November 14

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