ISSN 2278-3091
Volume 8, No.5, September - October 2019
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse91852019.pdf
https://doi.org/10.30534/ijatcse/2019/91852019

# Utilizing MINLP-based Hourly Dispatch Optimization on a Droop-Controlled Islanded Microgrid

**Lorwin Felimar B. Torrizo**[1], **Aaron Don M. Africa**[2]
Department of Electronics and Communications Engineering
De La Salle University, Manila
2401 Taft Ave., Malate, Manila 1004,
Philippines
[1]lorwin_torrizo@dlsu.edu.ph, [2]aaron.africa@dlsu.edu.ph

**ABSTRACT**

True to any profit-generating endeavors, the concept of reducing costs in order to maximize profit has always been there. In the context of islanded microgrids utilizing renewable energy, this comes in the form of reducing fossil fuel consumption, with the added bonus of also reduced $CO_2$ emissions. In the case of microgrids with multiple parallel operated diesel generators, there exists an optimal dispatch for the least amount of diesel consumed at any given loading condition. This paper presents a dispatch optimization algorithm for droop-controlled islanded microgrids in the form of a MINLP.

**Key words:** Dispatch, Optimization, MINLP, Microgrid

## 1. INTRODUCTION

### 1.1 Background

While the general concept of microgrids is nothing new, the increasing penetration of distributed generation, partly due to the rise of renewable energy usage, allowed microgrids to be a potentially profitable economic endeavor. The adoption of microgrids can offer several economic, environmental, and technical advantages; for consumers, these advantages are the availability and reliability of electricity, reduced emissions, and potentially lower electricity prices.

As a profit-driven venture, there is always an interest in keeping the costs low while maintaining the reliability of operation high. Within the context of microgrids, the operating costs is determined by how the resources are allocated in order to meet the required load (promptly called the dispatch). Identifying the best-case dispatch involves forecasting the upcoming demand and availability of resources and then allocating these resources in a way that reduces the cost of operation.

### 1.2 Motivation and Objectives of the Study

This study is intended to be a follow-up of an earlier study that focuses on electrical load forecasting on the context of microgrids. The previous study focused on properly predicting the upcoming parameters, such as the availability of electrical resource, environmental parameters, and historical load data, all utilized on determining the next-hour dispatch [1]. ANNs were the regression method of choice due to the non-linear nature of the parameters; furthermore, due to their flexibility, ANNs have already been utilized on several fields of application including clinical testing [2]–[5], security [6], identification [7], [8], and even traffic control [9].

This study, on the other hand, focuses on optimizing the dispatch of a microgrid for the next hour given the demand and availability of the resources. However, while similar studies about optimizing microgrid resources have already been done on the subject matter, few studies have done an optimization problem based on dispatch that revolves in controlling multiple parallel generator sets with differing fuel curves. The study aims to provide optimization on microgrids given this scenario, with an additional restriction that these gensets are droop-controlled: meaning that the load between the operational gensets are shared in proportion to their maximum capacity (i.e. same load percentage for every operating generator).

This specific scenario leads to different functions and constraints compared to the typical linear optimization found in majority of earlier dispatch optimization studies, which merits an investigation in itself. In addition, this study will offer a comparison between multiple solvers for the derived optimization problem.

## 2. RELATED LITERATURE

There is no shortage of previous studies that focuses on optimizing power system dispatch using various optimization methods not limited to microgrids. The focus of these studies are commonly oriented on reducing operational costs (termed as the economic dispatch or ED) but occasionally also aiming for the least emission (called the emission or environmental dispatch).

While being a relatively old study, the work of Gaing [10] remains one of the most referenced study related to economic dispatch. The study focuses on using Particle Swarm Optimization (PSO) as the method of choice on arriving with the ED considering the constraints of the generator(s). It concludes the paper by stating that PSO as being superior than Genetic Algorithm (GA) during tests. It should be noted, however, that their objective function is purely linear.

As another old study, Park et. al. [11] also did a PSO on ED with consideration for non-smooth cost function and compared with several other numerical methods, assessing that their derived modified PSO has shown superiority to other tested approaches.

Recent studies maintain the same concept but with a couple of variations. Studies such as [12] and [13] still focuses on ED but includes transmission losses. Some studies include environmental/emission reduction as part of the optimization such as [14] and [15].

It is necessary, however, to differentiate optimization schemes that focus on microgrids, as the dispatch constraints are different primarily due to the existence of energy storage systems (ESS), which [16] demonstrates by offering an in-depth analysis on how to define the costs within a DC microgrid, Some examples of studies involving dispatch optimization in microgrids are [17], [18], [19], and [20].

## 3. METHODOLOGY

### 3.1 Data gathering

#### *3.1.1 Modelling the Microgrid*

The single line diagram of the microgrid architecture to be used as a model in this study is shown in Figure 1.

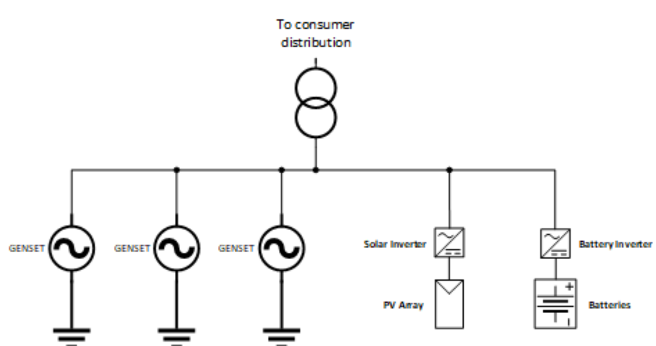


**Figure 1**: Microgrid Architecture for the Study

This microgrid design is loosely based from one of the microgrids in the country: the Paluan Microgrid in the island of Mindoro which also sports two megawatts of solar panels.

The microgrid model is primarily comprised of a 2MW PV array source, three different gensets with different ratings that have a combined capacity of around 1.9 MW, a Li-ion based energy storage system that can provide/accept 400kW while having a capacity of around 1.6 MWhr, and the necessary inverters for converting the resulting DC voltage from the PV array and batteries to AC and vice versa.

The components selected to represent some of the components is listed in Table 1.

**Table 1**: Specific Microgrid Components for Modelling

| Microgrid Component | Specific Model |
|---|---|
| Battery | Tesla Powerpack [21] |
| Diesel Generator 1 | Baudouin 6M33 [22] |
| Diesel Generator 2 | Atlas Copco QAC1100 [23] |
| Diesel Generator 3 | Volvo TAD1641GE [24] |

Each component has their own specification which affects their impact on the optimization of the microgrid model dispatch. These specs necessary for modeling the dispatch are listed below (Table 2).

**Table 2**: Specific Microgrid Components for Modelling

| Microgrid Component | Necessary Specifications |
|---|---|
| Battery | Max Power ($kW_c$, $kW_d$)<br>Max Storage (kWHr)<br>Efficiencies ($\eta_{batt,c}$, $\eta_{batt,d}$) |
| Diesel Generator/s | Max Power (kW)<br>Fuel Consumption (F) |

The max power of the diesel generators is represented by their corresponding characteristic curves. For approximation purposes, their characteristic curves can be represented by the following equation:

$$F = F_0 Y_{gen} + F_1 P_{gen} \tag{1}$$

#### *3.1.2 Meteorological Data and Hourly Load Profile*

In order to assess the viability of multiple optimization algorithms, a proper source of data related to microgrid operation is necessary.

Ideally, utilizing data obtained from an actual microgrid would be the best case. In real time, this may involve installation of monitoring systems. Such a concept can even extend to wireless sensor networks (WSN) [25], which by itself is another field of study that can has seen use from home automation [26] to weather tracking [27]. Multiple WSN-related studies have already been published, some relating to signal propagation between its nodes [28], [29].

However, since microgrids in general are run by private entities, it is hard to obtain permission to utilize sensitive information used by these companies. Thus, this study opts in using publicly available data. For irradiance values that represent the power from the PV array, the data was obtained from the National Renewable Energy Laboratory (NREL)

[30]. For the hourly electrical demand, information taken from the National Grid Corporation of the Philippines (NGCP) [31] will be normalized to fit the selected microgrid model. The location of the hypothetical microgrid is set to be located at the capital of the Philippines, Manila.

## 3.2 Optimization

### *3.2.1 Objective Function and Constraints*

The calculation of operational costs involves the following parameters and characteristics of equipment within the microgrid ecosystem:

- The (anticipated) available power from the PV array
- The (anticipated) next hour load
- The current available energy stored in the battery
- The specifications/characteristics of the components

There are several assumptions involved in the process, including:

- Outside of the efficiency ratings of the components stated above, other possible causes of electrical loss (such as wiring resistance, transformer, aging) are assumed negligible.
- The solar panels are installed horizontally with respect to the surface of the earth, meaning that the obtained Global Horizontal Solar Irradiance from NREL is useable in representing solar power.
- When more than one genset is dispatched, the gensets distribute the load between them through droop control, meaning that each genset assumes a portion of the load proportional to its rated power.

The primary aim of the optimization problem is to reduce operational cost by minimizing the diesel consumption, which is represented by the following objective function:

$$\min_{m_i \in \{0,1\}} D = \sum_{i=1}^{n} m_i\left(F_{0,i}Y_{gen,i} + F_{1,i}P_{gen,i}\right) \quad (2)$$

where $F_{0,i}Y_{gen,i} + F_{1,i}P_{gen,i}$ is the fuel consumption of genset i (if it was operational), $m_i$ is the state of operation of genset i (0 if off, 1 if on), and n the amount of gensets on the model.

The constraints are as follows:

$$P_{load} = P_{batt} + P_{PV} + P_{gen} \quad (3)$$

Equation (3) states that the amount of power supplied by the PV array ($P_{PV}$), the diesel generator ($P_{gen}$) and battery ($P_{batt}$, could be negative if charging instead) should be equal to the power demanded by the load ($P_{load}$).

$$P_{gen} = \sum_{i=1}^{n} m_i P_{gen,i} \quad (4)$$

The total amount of power supplied by the diesel generators is the sum of the individual power provided by the generators. It may seem that the binary variables ($m_i$) indicating the operation of each generator may seem redundant, but the following constraint necessitates the use of those variables.

$$\frac{P_{gen,1}}{P_{gen,max,1}} = \frac{P_{gen,2}}{P_{gen,max,2}} = \cdots = \frac{P_{gen,i}}{P_{gen,max,i}} \quad (5)$$

Equation (5) indicates the percentage of output of each generator with respect to their own maximum capacity should be equal between all generators. This constraint represents the droop control for parallel operation.

$$P_{gen,i} \le P_{gen,max,i} \quad (6)$$

Lastly, this constraint indicates that each individual generator has its own maximum capacity that it cannot exceed.

### *3.2.2 Other Constraints and Post-Processing*

There are two additional ‘should-be’ constraints that had to be given extra consideration due to their interaction with each other.

$$P_{PV} \le P_{PV}^{MPP} \quad (7)$$

$$-P_{batt,c/d} \le P_{batt} \le P_{batt,c/d} \quad (8)$$

Equation (7) indicates that the maximum power that the PV array can provide is limited by the maximum power point (MPP) that it can provide given the current irradiance. Equation (8) states that whether the battery is charging or discharging, the maximum that the battery can provide or intake is limited by the battery’s maximum charge/discharge power flow ($P_{batt,c/d}$). Furthermore, $P_{batt}$ is also bound by several other limits, such as its current contained charge and the maximum energy the battery can contain.

The dilemma between these two constraints is that in the scenario that there is excess power from the PV source, ideally it should be redirected to the battery if there is still room for charge. However, in order to achieve this would it would necessitate a separate function that maximizes charging power before tapering the amount drawn from the solar panels, possibly interfering with the original objective of reducing fuel consumption.

In order to simplify the solving process, $P_{PV}$ is instead set to its MPP while the lower bound of $P_{batt}$ was removed, and the remaining issues concerning charging power, actual energy provided by the PV array and the resulting energy stored in the battery (for use on the next hour iteration) was calculated post-optimization.

### *3.2.3 Solvers*

The resulting functions are comprised by binary and continuous variables, and is categorized as a Mixed Integer Non-Linear Programming (MINLP) problem. While there are multiple solver algorithms that can be used for such an optimization problem, this study opts in evaluating the three following deterministic MINLP solvers: SCIP, BONMIN, and BARON.

SCIP, short for Solving Constraint Integer Problems, is a software framework intended for constraint integer programming problems. Originally developed by T.Achterberg [32], SCIP touts itself as one of the fastest non-commercial solvers for Mixed Integer Programming (MIP) and MINLP. This study utilizes v5.0.1 [33] through the OPTI Toolbox [34].

BONMIN (Basic Open-source Nonlinear Mixed Integer Programming) is a dedicated general MINLP solver developed as part of a collaboration between Carnegie Mellon University and IBM Research [35]. Being the default MINLP of the aforementioned OPTI Toolbox, it is considered for this study due to its accessibility.

Lastly, BARON (Branch-and-Reduce Optimization Navigator) is a computational system for solving NLPs and MINLPs. Developed as early as 1996 [36], BARON has several publications connected to it [37] and is also accessible under MATLAB with an interface that can be utilized by the OPTI Toolbox.

The three methods above were evaluated by [38] with competitive results, while SCIP and BARON even rank high against other third-party MINLP benchmarks [39].

Initially, there was an attempt to include Genetic Algorithm (GA) as a comparison point representing heuristic solvers against the earlier stated deterministic solvers, but the implementation intended to be used (thru MATLAB's Optimization Toolbox [40]) does not accept integer programming combined with both linear and nonlinear equalities, and even after working around this limitation the documentation states that the procedure can fail [41]. Moreover, preliminary results showed that nearly 70% of the optimization iterations did not satisfy the constraints, and thus the idea of utilizing GA was abandoned entirely.

## 4. RESULTS AND DISCUSSION

The study utilizes hourly data for the whole month of December 2015, which equates to 744 data points to be solved. In order to evaluate the performance of the three MINLP solvers, both the capability to solve the function as well as the speed of each algorithm was measured.

Utilizing the tic toc function of MATLAB, it is possible to measure the amount of time it takes for the optimization function to arrive in a solution.

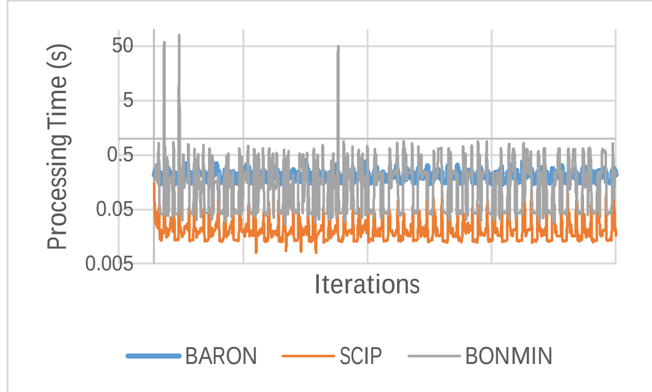


**Figure 2**: Processing Time per Iteration

**Table 3**: Geometric Mean of Execution Time

| **Geometric Mean of Execution Time** | | |
|---|---|---|
| **BARON** | **SCIP** | **BONMIN** |
| 0.20393 | 0.02066 | 0.12588 |

As shown in Figure 2 and Table 3, SCIP posted the fastest processing time out of the three. BONMIN, while having a geometric mean that is less than BARON, actually posted a higher average time to complete multiple iterations due to some outliers in the data.

**Table 4**: Successful Solution Finding

| **BARON** | **SCIP** | **BONMIN** |
|---|---|---|
| 100% | 100% | 91.13% |

On all iterations did BARON and SCIP found the solution to the optimization problem, and their respective results are 100% the same. BONMIN, on the other hand, found solutions for 678 out of the 744 iterations with very similar results to the other two (Table 4). Judging from the failed solutions, there seems to be an issue with resolving the integer programming part but even adjusting the relevant parameters did nothing to the results.

In order to validate the impact of the optimization, the results obtained through the presented MINLP can be compared with a non-optimized dispatch which relies on power reliability, in which all gensets will be providing power once the PV array and battery handle the demand by themselves.

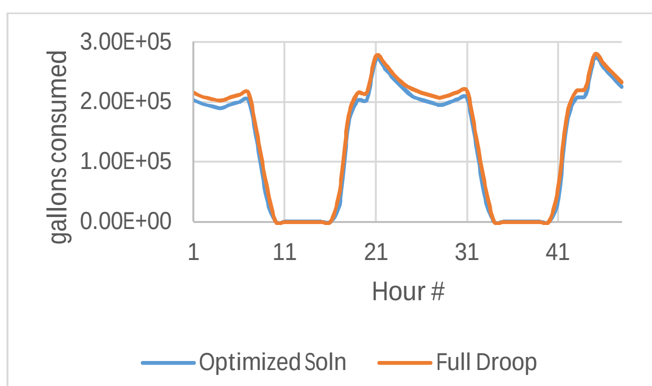


**Figure 3**: Gallons Consumed for the first 48 hours

**Table 5:** Total Diesel Consumption for the Month

| Total Gallons Consumed | |
|---|---|
| **Optimized** | **Full Droop** |
| 88188470.50 | 94662238.00 |

Comparing the diesel consumption of the two dispatch (Table 5) implementations shows the optimized dispatch consumes 6.84% less the amount of diesel compared to the reference.

## 5. CONCLUSION AND RECOMMENDATIONS

The study aimed to achieve an optimization algorithm that can reduce the operational cost of microgrids with droop-controlled gensets thru reduction of diesel consumption, and the results have shown that it was successful in doing so. While the study uses a specific configuration of a microgrid in order to demonstrate the problem, the derived MINLP problem can be utilized on any configuration of microgrids with multiple droop-controlled diesel generators.

Through the course of experimentation, multiple MINLP solvers were utilized and compared to each other, with SCIP coming out on top against BARON and BONMIN for this specific application. While these three solvers were judged to be enough for the purposes of this study, there are still multiple MINLP solvers that can be evaluated further, some accessible through GAMS distribution [42].

## REFERENCES

[1] L. F. Torrizo and A. D. Africa, “Next-hour electrical load forecasting using an artificial neural network: Applicability in the Philippines,” *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 3, pp. 831–835, 2019 https://doi.org/10.30534/ijatcse/2019/77832019.

[2] A. D. M. Africa and J. S. Velasco, “Development of a urine strip analyzer using artificial neural network using an android phone,” *ARPN J. Eng. Appl. Sci.*, vol. 12, no. 6, pp. 1706–1713, 2017.

[3] J. A. C. Jose, M. K. Cabatuan, E. P. Dadios, and L. A. G. Lim, “Stroke position classification in breast self-examination using parallel neural network and wavelet transform,” *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON*, vol. 2015-January, pp. 2–6, 2015. https://doi.org/10.1109/TENCON.2014.7022288

[4] J. A. C. Jose, M. K. Cabatuan, R. K. Billones, E. P. Dadios, and L. A. G. Lim, “Monocular depth level estimation for breast self-examination (BSE) using RGBD BSE dataset,” *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON*, vol. 2016-January, 2016. https://doi.org/10.1109/TENCON.2015.7372948

[5] R. A. A. Masilang, M. K. Cabatuan, E. P. Dadios, and L. G. Lim, “Computer-aided BSE torso tracking algorithm using neural networks, contours, and edge features,” *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON*, vol. 2015-January, no. 4, pp. 4–8, 2015. https://doi.org/10.1109/TENCON.2014.7022300

[6] P. K. Kollu and R. S. Prasad, “Effective Intrusion Detection using Deeper Recurrent Neural Networks,” *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 4, pp. 1134–1138, 2019. https://doi.org/10.30534/ijatcse/2019/21842019

[7] J. Del Espiritu, G. Rolluqui, and R. C. Gustilo, “Neural network based partial fingerprint recognition as support for forensics,” *8th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag. HNICEM 2015*, no. December, 2016.

[8] S. L. Rabano, M. K. Cabatuan, E. Sybingco, E. P. Dadios, and E. J. Calilung, “Common garbage classification using mobilenet,” *2018 IEEE 10th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag. HNICEM 2018*, pp. 1–4, 2019. https://doi.org/10.1109/HNICEM.2018.8666300

[9] A. D. Africa, F. X. Asuncion, J. L. Tiberio, and R. M. F. A. Muncha, “Sensor-based Traffic Control Network with Neural Network Based Control System,” *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 4, pp. 983–989, 2019. https://doi.org/10.30534/ijatcse/2019/01842019

[10] Z. L. Gaing, “Particle swarm optimization to solving the economic dispatch considering the generator constraints,” *IEEE Trans. Power Syst.*, vol. 18, no. 3, pp. 1187–1195, 2003.

[11] J. B. Park, K. S. Lee, J. R. Shin, and K. Y. Lee, “A particle swarm optimization for economic dispatch with nonsmooth cost functions,” *IEEE Trans. Power Syst.*, vol. 20, no. 1, pp. 34–42, 2005. https://doi.org/10.1109/TPWRS.2004.831275

[12] J. Rizwana, R. Jeevitha, R. Venkatesh, and K. S. Parthiban, “Minimization of fuel cost in solving the power economic dispatch problem including transmission losses by using modified Particle Swarm Optimization,” *2015 IEEE Int. Conf. Comput. Intell. Comput. Res. ICCIC 2015*, pp. 1–4, 2016.

[13] J. Tang, B. Sun, R. Chen, Y. Yao, and G. Wang, “Economic Dispatching Method Based on Dynamic Network Loss Factor,” *2018 Int. Conf. Power Syst. Technol. POWERCON 2018 - Proc.*, no. 1, pp. 601–605, 2019.

[14] P. Ajay-D-Vimal Raj, Y. Monica, S. Ansaar, and J. Pradeeban, “Population set based optimization method (PSBO) for economic and emission dispatch problems,” *Proc. 2015 IEEE Int. Conf. Power Adv. Control Eng. ICPACE 2015*, pp. 275–279, 2015.

[15] D. Maity, S. Ghosal, S. Banerjee, and C. K. Chanda, “Bare bones teaching learning based optimization for combined economic emission load dispatch problem,” *3rd Int. Conf. Electr. Electron. Eng. Trends, Commun. Optim. Sci. (EEECOS 2016)*, vol. 2, no. 1, 2018. https://doi.org/10.1049/cp.2016.1554

[16] I. U. Nutkani, W. Peng, P. C. Loh, and F. Blaabjerg, “Cost-based droop scheme for DC microgrid,” *2014 IEEE Energy Convers. Congr. Expo. ECCE 2014*, pp. 765–769, 2014. https://doi.org/10.1109/ECCE.2014.6953473

[17] C. Li, F. De Bosio, F. Chen, S. K. Chaudhary, J. C. Vasquez, and J. M. Guerrero, “Economic Dispatch for Operating Cost Minimization under Real-Time Pricing in Droop-Controlled DC Microgrid,” *IEEE J. Emerg. Sel. Top. Power Electron.*, vol. 5, no. 1, pp. 587–595, 2017. https://doi.org/10.1109/JESTPE.2016.2634026

[18] S. Ramabhotla, S. Bayne, and M. Giesselmann, “Economic dispatch optimization of microgrid in islanded mode,” *Int. Energy Sustain. Conf. 2014, IESC 2014*, vol. 2, pp. 2–6, 2014. https://doi.org/10.1109/IESC.2014.7061838

[19] N. Nikmehr and S. Najafi-Ravadanegh, “Probabilistic optimal power dispatch in multi-microgrids using heuristic algorithms,” pp. 1–6, 2015. https://doi.org/10.1109/SGC.2014.7151035

[20] Y. Jiang-Feng, W. Wei, and P. Yong-Gang, “A real-time optimal energy dispatch for microgrid including battery energy storage,” in *SKIMA 2016 - 2016 10th International Conference on Software, Knowledge, Information Management and Applications*, 2017, pp. 314–318. https://doi.org/10.1109/SKIMA.2016.7916239

[21] TESLA, “TESLA Powerpack Inverter,” 2018.

[22] G. Specifications and S. Equipment, “PowerKit Engine 6M33 Series PowerKit Engine 6M33 Series Dimensions and Weight.”

[23] ATLAS COPCO, “QAC 1100 TWINPOWER.” 2015.

[24] V. Penta, “TAD1641GE Genset Engine.” 2014.

[25] P. Rawat, K. D. Singh, H. Chaouchi, and J. M. Bonnin, “Wireless sensor networks: A survey on recent developments and potential synergies,” *J. Supercomput.*, vol. 68, no. 1, pp. 1–48, 2014.

[26] A. M. D. Celebre, A. Z. D. Dubouzet, I. B. A. Medina, A. N. M. Surposa, and R. C. Gustilo, “Home automation using raspberry Pi through Siri enabled mobile devices,” *8th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag. HNICEM 2015*, no. December, 2016. https://doi.org/10.1109/HNICEM.2015.7393270

[27] N. J. C. Libatique *et al.*, “Design of a tropical rain - Disaster alarm system: A new approach based on wireless sensor networks and acoustic rain rate measurements,” *2009 IEEE Intrumentation Meas. Technol. Conf. I2MTC 2009*, no. May, pp. 1341–1345, 2009. https://doi.org/10.1109/IMTC.2009.5168663

[28] D. D. N. Abinoja and L. Y. Materum, “BIC-based optimization of the identification of multipath propagation clusters in MIMO wireless systems,” *ISAP 2016 - Int. Symp. Antennas Propag.*, no. 1, pp. 428–429, 2017.

[29] H. C. Dy and R. C. Gustilo, “Characterization of signal response for surface water movements in underwater optical wireless communications,” *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON*, 2012.

[30] “Solar Position and Intensity | Grid Modernization | NREL.” [Online]. Available: https://www.nrel.gov/grid/solar-resource/solpos.html. [Accessed: 05-May-2019].

[31] “Operations - National Grid Corporation of the Philippines.” [Online]. Available: https://www.ngcp.ph/operations#operations. [Accessed: 05-May-2019].

[32] T. Achterberg, “SCIP: Solving constraint integer programs,” *Math. Program. Comput.*, vol. 1, no. 1, pp. 1–41, 2009. https://doi.org/10.1007/s12532-008-0001-1

[33] A. Gleixner *et al.*, “The SCIP Optimization Suite 5.0,” Takustr. 7, 14195 Berlin, 2017.

[34] J. Currie and D. I. Wilson, “OPTI: Lowering the Barrier Between Open Source Optimizers and the Industrial MATLAB User,” in *Foundations of Computer-Aided Process Operations*, 2012.

[35] “Bonmin Home Page.” [Online]. Available: https://www.coin-or.org/Bonmin/. [Accessed: 10-Oct-2019].

[36] N. V Sahinidis, “BARON: A general purpose global optimization software package,” *J. Glob. Optim.*, vol. 8, no. 2, pp. 201–205, 1996. https://doi.org/10.1007/BF00138693

[37] the optimization firm, “BARON publications.” [Online]. Available: https://minlp.com/baron-publications. [Accessed: 10-Oct-2019].

[38] J. Kronqvist, D. E. Bernal, A. Lundell, and I. E. Grossmann, “A review and comparison of solvers for convex MINLP,” *Optim. Eng.*, vol. 20, no. 2, pp. 397–455, 2019. https://doi.org/10.1007/s11081-018-9411-8

[39] H. Mittelmann, “Mixed Integer Nonlinear Programming Benchmark (MINLPLIB),” 2019. [Online]. Available: http://plato.asu.edu/ftp/minlp.html. [Accessed: 12-Oct-2019].

[40] “Optimization Toolbox - MATLAB.” [Online]. Available: https://www.mathworks.com/products/optimization.html. [Accessed: 13-Oct-2019].

[41] “Mixed Integer Optimization - MATLAB & Simulink.” [Online]. Available: https://www.mathworks.com/help/gads/mixed-integer-optimization.html. [Accessed: 10-Oct-2019].

[42] G. D. Corporation, “General Algebraic Modeling System (GAMS) Release 28.2.0.” 2019.