Load Modelling Using Affine Arithmetic for Demand Side Management

Fernanda Ávila
Universidad de Chile
Electrical Engineering Department
Santiago, Chile
Email: favila@ing.uchile.cl

Claudio Cañizares
University of Waterloo
Department of Electrical and Computer Engineering
Waterloo, Canada
Email: ccanizares@uwaterloo.ca

Doris Sáez
and Felipe Valencia
Universidad de Chile
Solar Energy Research Center SERC-Chile
Santiago, Chile
Email: dsaez@ing.uchile.cl
felipe.valencia@sercchile.cl

***Abstract*—Demand side management (DSM) programs aim at reducing energy consumption on the demand side, which benefits both consumers and utilities. These programs could also help maintain the critical balance between generation and demand in isolated microgrids. In this case, demand is a treated as a significant uncertainty in the context of dispatching the power resources of a microgrid. Thus, in this paper the uncertainty of consumer response to DSM signals are treated as intervals to represent the corresponding range of variation based on affine arithmetic. The total range of total grid consumption is taken as the sum of intervals in each house, using data obtained through surveys regarding usage of appliances to obtain the individual consumer intervals. The proposed affine arithmetic model is then applied to the prediction of possible range variation in a one-day ahead load forecast. Finally, the presented technique is demonstrated using data obtained in an actual microgrid deployed in Huatacondo, Chile.**

I. Introduction

Microgrids have demonstrated being an alternative for the integration of renewable energy resources in the current electric distribution systems. Microgrid is a current concept that denotes the operation and interactions between a cluster of loads and a set of different small generators that provide both power and heat to a local area [1]. Microgrids are able to operate in connected or isolated mode. In the former, an utility supports the operation of the microgrid. In the later, the demand should be attended using the local energy resources. In this paper only isolated microgrids are considered.

In isolated microgrids both energy sources and the demand should be coordinated for a safe operation. With this purpose, demand side management (DSM) strategies are often used [2]. In microgrids, DSM programs consists on a series of activities performed by the system operator to maintain the balance between the available energy and the demand. These activities should allow effective access to green energy, taking actions such as reducing demand peaks, valleys filling, increase strategic load, and moving demand blocks in flexible loads [3].

Isolated microgrids offer a broad set of alternatives for the electrification of remote settlements [4]. However, it has been found that, given their small size, changes in the use of appliances in homes can have an effect on power levels, and thus on the operation of microgrids. Therefore, there is a need for accurate load forecasts for their safe scheduling, planning, and management [5]. Accordingly, the uncertainty associated with the response of the consumers to the DSM signals should be modelled and how the load would change must be estimated.

One way to estimate the load behaviour is using empirical models. In [6], a complete survey about load forecasting methodologies is presented. Furthermore, in [7]–[9] the authors reviewed and compared different load forecasting methodologies. Notwithstanding the forecasting capabilities demonstrated by the load models reported in the literature, little attention has been paid to the possible changes in the demand because of DSM. Indeed, since price signals are an important DSM technique [10], [11], in [3] household load profiles are generated to simulate the changes in the load profile of houses that are equipped with smart appliances and time-based electricity prices. However, in certain environments these types of signals may not be feasible [12], [13]. For instance, in [13] the demand warning clock described in [12] is used as a DSM signal of an Energy Management System (EMS), so that consumers adjust their power demand accordingly.

This paper presents a load forecasting methodology based on affine arithmetic (AA). AA is an enhanced model for self-validating numerical analysis in which the quantities of interest are represented as affine combinations (affine forms) of certain primitive variables, which stand for sources of uncertainty in the data [14]. AA was selected because these models keep track of correlations between computed and input quantities. Therefore, it is robust with respect to the loss of accuracy often observed in long interval computations [14]. The use of AA is not new. In fact, in large power systems AA has been proposed to model uncertainties through the use of intervals [14]–[16]. In this way, the use of probability functions was avoided. In [15], an AA-based power flow technique was presented, and in [14], [16] AA-based optimal power flow (OPF) approaches were described.

The rest of this paper is structured as follows: In Section II the proposed method for load modelling is explained together with a brief introduction to AA. Section III presents the results

978-1-4673-6605-2/15/$31.00 ©2015 IEEE

of applying the proposed technique to the estimation of load profile ranges in the microgrid of Huatacondo, Chile, using actual collected survey data. Finally, Section IV presents the main conclusions and contributions of this work.

II. Proposed Method for Load Modelling

The current investigation involved the development of a load forecasting methodology for isolated microgrids. Load forecasting is important for the safe operation of isolated microgrids because any change in the consumption pattern might produce a generation-demand unbalance. Due to its uncertainty, load forecasting is not an easy task. In order to include the uncertainty, an interval model was proposed using AA. In AA, a partially unknown quantity is represented by an affine form using the following first degree polynomial:

$$\hat{x} = x_{\mathrm{o}} + x_1\epsilon_1 + \ldots + x_n\epsilon_n \tag{1}$$

where x_{o} is the central value, and the parameters $x_i,\ i = 1,\ldots,n$ are known real coefficients that may be represented by partial deviations obtained from sensitivity analysis or other measures. The variables $\epsilon_i,\ i = 1,\ldots,n$ stand for independent sources of uncertainty, each contributing to the total uncertainty of the quantity x, and are assumed to lie inside the interval $[-1,1]$.

Since isolated microgrids generally are smaller conducting a survey is proposed to determine the range of the load variation. The survey provides the expected response of the customers because of the DSM, which in this case, is the source of uncertainty. Thereby, the intervals of the AA model are determined by the extreme levels of consumption obtained from the survey. For the house i at the hour k, let $\hat{L}_{ik}$ denotes the estimated consumption, $L_{\mathrm{o}ik}$ denotes the load value corresponding to the base case (without DSM), ϵ_{jk} denotes the uncertainty of the variation of the consumption associated to the DSM signal j, and L_{jik} denotes the sensitivity to the DSM signal j. Then, power consumption at house i and hour k is represented in affine form with respect to terms that model the uncertainty as follows:

$$\hat{L}_{ik} = L_{\mathrm{o}ik} + \sum_{j\in\Omega} \epsilon_{jk} L_{jik} \tag{2}$$

with $i = 1,\ldots,n$, $k = 1,\ldots,24$, and Ω the set of DSM signals (or actions); n being the number of houses fed by the microgrid.

From (2), the interval of each house at hour k has the following form:

$$[\hat{L}_{ik}] = \left[L_{\mathrm{o}ik} - \sum_{j\in\Omega} |L_{jik}|, L_{\mathrm{o}ik} + \sum_{j\in\Omega} |L_{jik}| \right] \tag{3}$$

where $|L_{jik}|$ is the total deviation of the affine form $\hat{L}_{ik}$. Furthermore, the total interval for the load at each hour k corresponds to the sum of the intervals for each house at that hour, as follows:

$$[L_k] = \sum_{i=1}^{n} \left[L_{\mathrm{o}ik} - \sum_{j\in\Omega} |L_{jik}|, L_{\mathrm{o}ik} + \sum_{j\in\Omega} |L_{jik}| \right] \tag{4}$$

In (4), $L_{\mathrm{o}ik} - \sum_{j\in\Omega} |L_{jik}|$ defines the lower boundary for L_k while $L_{\mathrm{o}ik} + \sum_{j\in\Omega} |L_{jik}|$ defines the upper boundary. In the specialized literature several approaches have been reported that provide similar results. In [17]–[19] for instance, different approaches to obtain interval model for load forecasting have been proposed. In these methods, historical datasets were used to derive the intervals. By contrast, the proposed approach uses the expected response of the customer to define the width of the interval. Furthermore, almost all approaches reported in the literature use numerical variables to represent the uncertainty. As it is shown in Section III, the proposed approach manages both numerical and non-numerical variables. This is important because the actions associated with the DSM not always involve numerical variables. Next Section presents the results obtained with the proposed methodology in Huatacondo, an isolated settlement at the north of Chile.

III. Application and Results

Results obtained in previous studies [17]–[19] using interval models indicated that they are able to adequately represent the uncertain behaviour of the load in microgrids. In this study, interval models were obtained for load forecasting using AA. Specifically, a methodology for obtaining load models for isolated microgrids was proposed. In this methodology, the DSM signals are used to evaluate the response of the customers. The evaluation is carried out by survey. Given the results of the survey, the range of load variation is determinate and the interval model is formulated.

The proposed methodology was evaluated in Huatacondo, an isolated Chilean community located in the Tarapaca region, 230 km southeast of Iquique. In this community an isolated microgrid was installed to provide 24-hour/day electricity service. This microgrid is composed of a photovoltaic system; a wind turbine; the existing diesel generator unit of the village; an energy storage system (ESS); a water pump; and a total of 17 houses whose total maximum demand is about 10 kW [13]. The microgrid also includes an EMS with DSM capabilities. The DSM sends signals to consumers through clocks installed at their homes, as shown in Fig. 1. The color represents the action to be taken: red indicates that the power consumption should be reduced, yellow indicates maintaining power consumption, and green indicates that power consumption may be increased. These DSM signals are meant to change the consumption patterns of consumers, thus affecting the predicted demand.

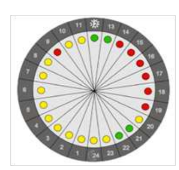
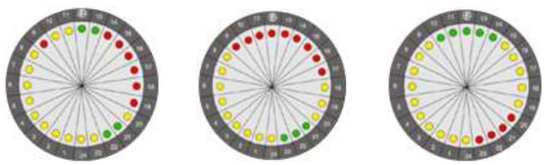


Fig. 1: Clock installed in consumers' households.

To obtain the necessary data for modeling the load variations, surveys were conducted in the 17 households, which correspond to all of the houses inhabited at the time of the survey. Since the survey involved the entire population the results obtained have statistical significance despite the reduced number of participants. Consumers were asked about their base electricity consumption (without the clock), and then three clocks with different sequences of color were shown to them, representing a sunny day (Fig. 2a), a cloudy day (Fig. 2b), and an abnormal day (Fig. 2c).



(a) (b) (c)

Fig. 2: Clocks used to conduct the survey in Huatacondo.

The color sequences were generated based on the signals sent by the EMS corresponding to the weather conditions (i.e. sunny or cloudy days). To generate the color sequence of the abnormal day, several signal sequences sent by the EMS were analyzed to identify common patterns for sunny and cloudy days, and thus opposite patterns were used to generate the clock shown in Fig. 2c. Using the information from the survey, the load variations between the base case and the various color lights (green, yellow or red) were calculated for each of the 17 houses at every hour. These variations were computed using the typical consumption rates presented in Table I. In this Table, only the appliances used by the inhabitants of Huatacondo were considered.

TABLE I: Typical consumption of the appliances used by the inhabitants of Huatacondo.

	Power $[W]$
Appliance:	
Refrigerator	350
Electric oven	1000
Kettle	1000
TV	70
Iron	1000
Light bulb	20
Washing machine	395
Stereo	120
Saw	1200
Drill	500
Microwave	1000

Table II presents the results of the survey for house 5, for instance. As can be seen, the maximum load variations in this house are at 19:00 and 20:00 hours. During the remaining hours slightly variations on the demand are exhibited. Indeed, several hours present no change despite of the changes in DSM signals. For instance, from 13:00 to 18:00 no variations on the demand were reported. As expected, house 5 presented some variations on the consumption pattern because of the DMS. A similar response was evidenced in the remaining houses. Table III depicts the result for every house at 11:00 AM. In this case, houses 3, 6, 11, 12, 13, and 17 presented changes in their consumption pattern due to the DSM. Moreover, based on the values presented in Table III, the affine form for each house can be calculated as for example:

TABLE II: Results of the survey for house 5. Here R, K, B, E, and I stand for refrigerator, kettle, light bulb, electric oven, and iron respectively.

	Case				Min Power	Max Power
	Base	(a)	(b)	(c)	[kW]	[kW]
Hour:						
7 : 00	R	R	K-R	R	0.1026	0.1471
8 : 00	R	R	R	R	0.1026	0.1026
9 : 00	R	R	R	R	0.1026	0.1026
10 : 00	K-R	K-R	R	K-R	0.1026	0.1471
11 : 00	R	R	R	R	0.1026	0.1026
12 : 00	R	R	R	R	0.1026	0.1026
13 : 00	K-TV	K-TV	K-TV	K-TV	0.2093	0.2093
	R	R	R	R		
14 : 00	R	R	R	R	0.1026	0.1026
15 : 00	R	R	R	R	0.1026	0.1026
16 : 00	R	R	R	R	0.1026	0.1026
17 : 00	K-TV	K-TV	K-TV	K-TV	0.2093	0.2093
	R	R	R	R		
18 : 00	TV-R	TV-R	TV-R	TV-R	0.1648	0.1648
19 : 00	TV-R	TV-R	TV-R	TV-R	0.6093	1.0537
	I	I	E	I		
20 : 00	TV-R	TV-R	TV-R	K-TV	0.2055	0.7055
	E-B	E-B	B	R-B		
21 : 00	K-TV	K-TV	TV-R	K-TV	0.2055	0.2555
	R-B	R-B	B	R-B		
22 : 00	R-B	R-B	R-B	R-B	0.1355	0.1355
23 : 00	R-B	R-B	R-B	R-B	0.1355	0.1355
24 : 00	R-B	R-B	R-B	R-B	0.1355	0.1355

TABLE III: Household load variations in kW at 11:00.

	Color		
	Green ($i = 1$)	Yellow ($i = 2$)	Red ($i = 3$)
House:			
1	0	0	0
2	0	0	0
3	0.395	0.395	0
4	0	0	0
5	0	0	0
6	0	0	-0.5
7	0	0	0
8	0	0	0
9	0	0	0
10	0	0	0
11	0	0	-0.19
12	0	0	-0.07
13	0.395	0	0
14	0	0	0
15	0	0	0
16	0	0	0
17	0.395	0	0

$$\hat{L}_{3,11} = L_{o,3,11} + 0.395\epsilon_{1,11} + 0.395\epsilon_{2,11} + 0\epsilon_{3,11} \quad (5)$$

$$\hat{L}_{6,11} = L_{o,6,11} + 0\epsilon_{1,11} + 0\epsilon_{2,11} - 0.5\epsilon_{3,11} \quad (6)$$

In (5) and (6), the terms $0\epsilon_{3,11}$ and $0\epsilon_{1,11}$ and $0\epsilon_{2,11}$ indicate that $\hat{L}_{3,11}$ is independent of the red light, whereas $\hat{L}_{6,11}$ is independent of both green and red lights. Hence, at 11:00 AM, House 3 would not make any change if they saw a red light, but they would increase or maintain their load in the presence of a green or yellow light. Since the values of ϵ can be at the limit equal to 0 and 1, the maximum and minimum loads can be defined as follows:

$$L_{ik\text{Max}} = L_{oik} + \max\{|\Delta L_{1ik}|, |\Delta L_{2ik}|, |\Delta L_{3ik}|\} \quad (7)$$

$$L_{ik\text{Min}} = L_{oik} + \min\{|\Delta L_{1ik}|, |\Delta L_{2ik}|, |\Delta L_{3ik}|\} \quad (8)$$

Expressions (7) and (8) define the maximum change the consumers are willing to make, by either increasing or decreasing the load. Adding the intervals of every house for each hour, and using the forecasted load as the base load of the entire microgrid, an upper and lower bound can be found for the expected variation in electrical consumption. Figure 3 shows the load forecast 96 steps ahead with the calculated intervals from the survey for the whole microgrid. The survey starts at 7:00 AM, which explains why there is no interval between midnight and 6:00 AM (steps 0 to 24). It is important to remark that the affine forms (5) and (6) involved non-numerical variables. In fact, variables $\epsilon_{1,11}$, $\epsilon_{2,11}$, and $\epsilon_{3,11}$ refer to green, yellow, and red color signals send by the DSM to the customers. This represents an advantage over the reported load forecasting models, since DSM schemes not always involve numerical variables. Furthermore, based on interval models robust schemes can be developed for the operation of isolated microgrids, in which the solution is robust against all realizations of the uncertain data within a deterministic uncertain set [20]. Notwithstanding the advantages of AA over other methods, its performance is highly dependent on the quality of the data used for parameter identification. This is evident in Fig. 3 at time step 80, where the accuracy of the prediction made using AA decreases; this time step coincides with the $20:00$ hour, at which time, the inhabitants of Huatacondo carry out several activities probably not captured by the survey.

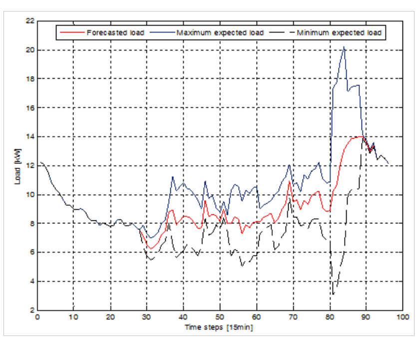


Fig. 3: Interval based on the AA model from the surveys.

IV. Conclusion

DSM signals affect the demand pattern and therefore the load forecasting. The DSM load variations were modeled using affine arithmetic in this work, with the objective of using it to correct the load forecast. An interval for the possible load variation was obtained as a result of application of the proposed method. The data was obtained through surveys given to the consumers of a microgrid installed in the community of Huatacondo, Chile. There are plans to carry out a comparison between the intervals obtained with the propose AA model and a fuzzy interval method that considers real load data when the consumers are using the DSM clocks, using the real behavior of consumers plus the answers of the survey to compare methods and evaluate the advantages and disadvantages of AA.

Acknowledgment

This research has been supported by the FONDECYT project Design of Robust Predictive Control Strategies for the Operation of Microgrids with High Penetration of Renewable Sources, grant number 1140775; by the FONDAP project Solar Energy Research Center SERC-Chile, grant number 15110019; by the WISE at the University of Waterloo; and the Energy Center at the Universidad de Chile.

References

[1] R. Lasseter, "Microgrids," in *Power Engineering Society Winter Meeting, 2002. IEEE*, vol. 1, 2002, pp. 305–308 vol.1.

[2] H. Nilsson, "The many faces of demand-side management," *Power Engineering Journal*, vol. 8, no. 5, pp. 207–210, Oct 1994.

[3] S. Gottwalt, W. Ketter, C. Block, J. Collins, and C. Weinhardt, "Demand side managementa simulation of household behavior under variable prices," *Energy Policy*, vol. 39, no. 12, pp. 8163–8174, 2011.

[4] K. Ubilla, G. Jimenez-Estevez, R. Hernádez, L. Reyes-Chamorro, C. Hernandez Irigoyen, B. Severino, and R. Palma-Behnke, "Smart microgrids as a solution for rural electrification: Ensuring long-term sustainability through cadastre and business models," 2014.

[5] P. P. Chan, W.-C. Chen, W. W. Ng, and D. S. Yeung, "Multiple classifier system for short term load forecast of microgrid," in *2011 International Conference on Machine Learning and Cybernetics (ICMLC)*, vol. 3. IEEE, 2011, pp. 1268–1273.

[6] H. K. Alfares and M. Nazeeruddin, "Electric load forecasting: literature survey and classification of methods," *International Journal of Systems Science*, vol. 33, no. 1, pp. 23–34, 2002.

[7] A. Khosravi, S. Nahavandi, D. Creighton, and D. Srinivasan, "Interval type-2 fuzzy logic systems for load forecasting: a comparative study," *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1274–1282, 2012.

[8] H. Hahn, S. Meyer-Nieberg, and S. Pickl, "Electric load forecasting methods: Tools for decision making," *European Journal of Operational Research*, vol. 199, no. 3, pp. 902–907, 2009.

[9] A. Ghanbari, E. Hadavandi, and S. Abbasian-Naghneh, "Comparison of artificial intelligence based techniques for short term load forecasting," in *2010 Third International Conference on Business Intelligence and Financial Engineering (BIFE)*. IEEE, 2010, pp. 6–10.

[10] M. G. Lijesen, "The real-time price elasticity of electricity," *Energy economics*, vol. 29, no. 2, pp. 249–258, 2007.

[11] O. Corradi, H. Ochsenfeld, H. Madsen, and P. Pinson, "Controlling electricity consumption by forecasting its response to varying prices," *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 421–429, 2013.

[12] R. Palma-Behnke, D. Ortiz, L. Reyes, G. Jimenez-Estevez, and N. Garrido, "A social scada approach for a renewable based microgridthe huatacondo project," in *Power and Energy Society General Meeting, 2011 IEEE*. IEEE, 2011, pp. 1–7.

[13] R. Palma-Behnke, C. Benavides, E. Aranda, J. Llanos, and D. Saez, "Energy management system for a renewable based microgrid with a demand side management mechanism," in *2011 IEEE symposium on Computational intelligence applications in smart grid (CIASG)*. IEEE, 2011, pp. 1–8.

[14] A. Vaccaro, C. A. Canizares, and D. Villacci, "An affine arithmetic-based methodology for reliable power flow analysis in the presence of data uncertainty," *IEEE Transactions on Power Systems*, vol. 25, no. 2, pp. 624–632, 2010.

[15] A. Vaccaro, C. A. Cañizares, and K. Bhattacharya, "A range arithmetic-based optimization model for power flow analysis under interval uncertainty," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 1179–1186, 2013.

[16] M. Pirnia, C. A. Cañizares, K. Bhattacharya, and A. Vaccaro, "An affine arithmetic method to solve the stochastic power flow problem based on a mixed complementarity formulation," in *2012 IEEE Power and Energy Society General Meeting*. IEEE, 2012, pp. 1–7.
[17] C. Guan, P. B. Luh, L. D. Michel, and Z. Chi, "Hybrid kalman filters for very short-term load forecasting and prediction interval estimation," 2013.
[18] H. Quan, D. Srinivasan, and A. Khosravi, "Short-term load and wind power forecasting using neural network-based prediction intervals," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 25, no. 2, pp. 303–315, 2014.
[19] N. A. Shrivastava, A. Khosravi, and B. K. Panigrahi, "Prediction interval estimation for electricity price and demand using support vector machines," in *2014 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2014, pp. 3995–4002.
[20] D. Bertsimas, E. Litvinov, X. A. Sun, J. Zhao, and T. Zheng, "Adaptive robust optimization for the security constrained unit commitment problem," *Power Systems, IEEE Transactions on*, vol. 28, no. 1, pp. 52–63, 2013.