International Journal of Smart Grid and Clean Energy

# Managing residential demand uncertainty in a smart grid-interactive hydrokinetic river system

Sandile Phillip Koko [a], Kanzumba Kusakana [a], Tebello Mathaba [b]

[a] *Department of Electrical Engineering, Central University of Technology, Bloemfontein 9300, South Africa*
[b] *Department of Electrical Engineering, Vaal University of Technology, Vanderbijlpark 1911, South Africa*

**Abstract**

The aim of this paper is to provide an integrated optimization and control algorithm in order to solve the residential load demand uncertainty problem as encountered in a grid-interactive hydrokinetic river (GHR) system. The proposed GHR system is incorporated with a pumped hydro-storage system (PHS) to store excess energy. The proposed algorithm aims to resolve the load demand uncertainty in order to minimize the electricity bills of the consumer and to maximize the energy sales into the grid, under time-of-use (TOU) tariff scheme. Therefore, the maximization of load demand satisfaction is not compromised. The traditional open loop optimization approach cannot cater for load demand uncertainty. It becomes more challenging to adequately meet the uncertain load demand. Within this context, the rule-based control algorithm is developed to manage power flow during uncertain load demand. The obtained results demonstrated that the load demand is adequately met at a reduced grid consumption cost, through the application of the rule-based control algorithm. This confirmed that the proposed algorithm benefits the user, by reliably and economically satisfying the load demand at a minimal grid energy cost.

*Keywords: Hydrokinetic, time-of-use, load demand uncertainty, rule-based algorithm*

## 1. Introduction

Energy planning is critical to ensure a reliable energy supply system. Electric utility companies are facing an ever-increasing load demand challenge due to population growth [1]. Population growth may also result into increased probability of load demand uncertainty. Electric utility companies employ demand side management (DSM) programs to better make use of the existing power generation capacity [2,3]. Time-of-use (TOU) is the most widely adopted DSM technique used to encourage users to reduce their demand during peak demand hours. During peak hours, price of electricity is higher when compared to standard and off-peak hours. However, the disadvantage is that users may not always respond to the change in electricity price in order to optimize the electricity usage. Hence, the best approach is to equip users with an automatic control/responsive system instead of manual control.

With the normal open-loop optimization technique, it is difficult to meet the uncertain load demand. The reason being that it relies heavily on prediction precision. This could lead to undesired system operation [4]. Hence, a close-loop approach such as model predictive control (MPC) is applied [5]. However, MPC requires accurate load forecasting to achieve the objectives [6]. Accurate load forecasting is very difficult due to factors such as a change in weather condition and holidays [7]. In this context, a rule-based control algorithm is used in this study to address the load demand uncertainty problem. The rule-based algorithm relies on real-time measurements than relying on forecasting data [8].

Large amount of energy consumption is due to household and commercial sectors [9]. Therefore, bringing energy savings in such sectors is very critical. Consumers from such sectors may utilize their onsite grid-interactive renewable energy generation system to lower their energy consumption bills. On other hand, a grid-interactive generation system may be integrated with the energy storage system. The

* Manuscript received December 6, 2019; revised September 7, 2020.
Corresponding author. *E-mail address*: kuskybe@gmail.com.
doi: 10.12720/sgce.9.5.924-929

aim is to store excess energy during inexpensive off-peak periods. The stored energy can then be utilized during expensive peak period to supply the unmet load demand or be sold into the grid. Hydrokinetic is a promising renewable energy technology that has gained considerable attention these days. In this paper, a grid-interactive hydrokinetic river (GHR) system consisting of the pumped-hydro storage (PHS) system is used to store excess energy. The proposed system is used to supply the typical residential load and supplemented by the utility grid. In this paper, a real-time rule-based control algorithm is developed to solve the load demand uncertainty by minimizing the energy bills of the residential consumer.

## 2. Proposed System Layout and TOU Tariffs

As mentioned that the proposed system consists of the GHR system with a PHS system as shown in Fig. 1. The supplied load demand is variable for the studied nine days' period [10]. The load demands electricity from three different energy sources such hydrokinetic $P_{1(t)}$, PHS system $P_{2(t)}$, and the utility grid $P_{3(t)}$. The PHS stores excess energy from the hydrokinetic system $P_{4(t)}$ and can also be recharged using utility grid $P_{5(t)}$ during the affordable off-peak periods. Additionally, the excess energy from the hydrokinetic system $P_{6(t)}$ and PHS system $P_{7(t)}$ can be sold into the grid. The optimal energy management of the proposed system was developed in the previous study [11]. However, the behavior of the developed optimization model was not analyzed under load demand uncertainties since the open-loop optimization approach has been used. The simulation parameters to be used in this study, are as shown in Table 1.

### *2.1. Hydrokinetic system*

Hydrokinetic system generates electricity by making use of the kinetic energy of the flowing water resource to drive the underwater turbines. The operation principle is like the one of wind generation systems. The main discrepancy is that the water density is 800 times greater than the air density. Hence, large amount of electricity can be generated at very low water speeds (0.5 m/s and above) [12,13,14].

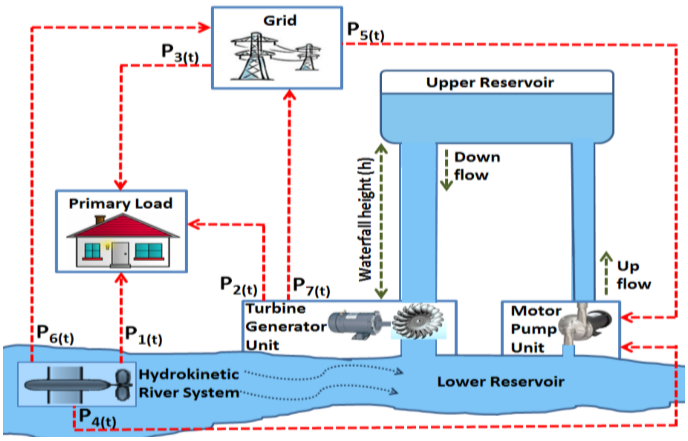


Fig. 1. Grid-interactive hydrokinetic river system with a pumped-hydro storage system

Table 1. Simulation parameters of the proposed Grid-interactive system

| Item | Value |
|---|---|
| Sampling time (Δt) | 30 minutes |
| Total number of sampling intervals (N) | 432 |
| PHS nominal capacity | 3 kWh |
| PHS maximum volume | 100% |
| PHS minimum volume | 5% |
| Initial upper reservoir capacity | 50% |
| Overall efficiency of the PHS | 70.6% |
| Hydrokinetic system size | 3 kW |

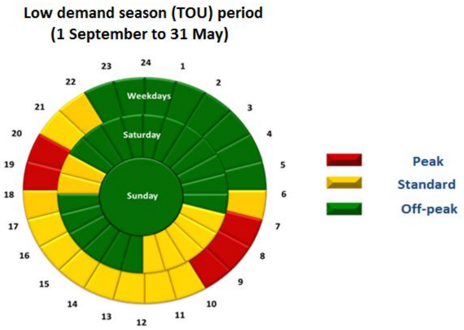


Fig. 2. TOU period for high demand season [15]

*2.2. Pumped-hydro storage*

The PHS system stores electrical energy by elevating certain volume of water from the lower reservoir (river) to the upper reservoir using the motor-pump system. The stored water can then be released later to generate electricity using the turbine generator unit [16,17].

*2.3. Time-of-use tariff rates and periods*

The TOU tariff period as used by the South African power utility company, have been applied as shown in Fig. 2 [15]. During low demand season, the tariff charges (using South African currency) are ZAR1.07/kWh, ZAR0.74/kWh and ZAR0.47/kWh during peak, standard, and off-peak period, respectively. During the study, 1US$ was equivalent to ZAR14.30.

**3. Proposed Algorithm**

As mentioned earlier that the rule-based algorithm is developed to solve the load demand uncertainty problem. The aim is to ensure that the uncertain load demand is reliably and economically met at all time. The predicted power variables are presented using the subscript *P*, while the actual ones are presented without the subscript *P*. Letter *r* is used to represent the sampling interval during rule-based control algorithm. The sampling interval ranges between *1* and *N*. The rule-based control algorithm will be tested using low demand season data. The uncertainty problem is solved through the application of the following criteria.

*3.1. When the actual load demand is more than predicted*

In cases whereby, the actual load demand is more than predicted, the three energy sources should be given priority orders to meet the unmet load demand. The predicted hydrokinetic-to-load power ($P_{P1}$) is increased as a priority to meet the unmet load demand. Hence, it should be adjusted to a new/actual value, ($P_1$). Hence, the predicted grid-to-load power ($P_{P3}$) and turbine-generator-to-load power ($P_{P2}$) are permitted to be constant as shown in Eq. (1). Hence, the new value should not exceed the rated power of the hydrokinetic system, as shown by Eq. (2). If the adjusted hydrokinetic power is not enough to meet the actual demand, the predicted PHS-to-load power is the next option to be increased and followed by the grid-to-load power, as shown by Eq. (3) and (4), respectively.

$$P_{1(r)} = P_{Load(r)} - P_{P2(r)} - P_{P3(r)} \qquad (1 \le r \le N) \tag{1}$$

$$P_{1(r)} = \min((P_{Load(r)} - P_{P2(r)} - P_{P3(r)}), (P_{P1(r)} + P_{P4(r)} + P_{P6(r)})) \qquad (1 \le r \le N) \tag{2}$$

$$P_{2(r)} = \min((P_{Load(r)} - P_{1(r)} - P_{P3(r)}), (P_{P2(r)} + P_{P7(r)})) \qquad (1 \le r \le N) \tag{3}$$

$$P_{3(r)} = P_{Load(r)} - P_{1(r)} - P_{2(r)} \qquad (1 \le r \le N) \tag{4}$$

### *3.2. When the actual load demand is less than predicted*

In cases whereby, the actual load demand is less than predicted, the open loop optimization model leads to excessive energy supply. Hence, the supplied load power needs to be reduced. The power reduction needs to be economically achieved by firstly reducing the costly one (e.g. the grid-to-load) and concluding with the affordable one (hydrokinetic-to-load). Hence, the predicted grid-to-load ($P_{P3}$) is reduced to a new actual value ($P_3$), while maintaining the two other sources constant, as shown by Eq. (5). After reducing or discontinuing $P_{P3}$ it may happen that the actual power is still more than the demanded one. Hence, the next step is to reduce hydrokinetic-to-load ($P_{P1}$) to a new value, as shown by Eq. (6). Should it happen than the supplied power is still more than the demanded one, then the predicted PHS-to-load power is then discontinued, as shown by Eq. (7).

$$P_{3(r)} = \max(0, (P_{Load(r)} - P_{P1(r)} - P_{P2(r)})) \qquad (1 \le r \le N) \tag{5}$$

$$P_{1(r)} = \max(0, P_{Load(r)} - P_{P2(r)}) \qquad (1 \le r \le N) \tag{6}$$

$$P_{2(r)} = zeros(1,1) \qquad (1 \le r \le N) \tag{7}$$

### *3.3. When the actual load demand is as predicted*

In cases whereby, the actual load demand is as predicted, the won't be any power shortage of excessively supplied power. All power variables are then maintained as predicted, as shown by Eq. (8).

$$P_{i(r)} = P_{Pi(r)} \qquad (1 \le i \le 7) \qquad (1 \le r \le N) \tag{8}$$

## 4. Results and Discussion

As mentioned earlier that the rule-based algorithm is developed to solve the residential load demand uncertainty. The main idea is always to allow the actual load demand to be met. 9 days' residential load profile is as shown in Fig. 3. for the residential load. The red dotted line reveals the actual load demand while the black solid lines represents the predicted demand during open-loop optimization approach. On other days the predicted demand is more than the actual one, while it is vice versa on other days.

During the evening peak period of the first Monday, the actual load demand is less that the predicted one, as shown in Fig. 3. Hence, this leads to a power shortage. As a result, the control algorithm increased the hydrokinetic power and PHS power as priority options for supplementing the load demand as shown in Fig. 5. The grid-to-load power is therefore maintained constant, as shown in Fig. 4.

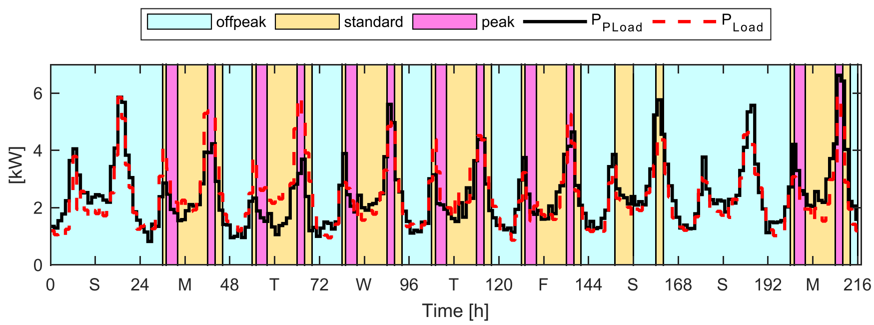


Fig. 3. Predicted and actual residential load demand

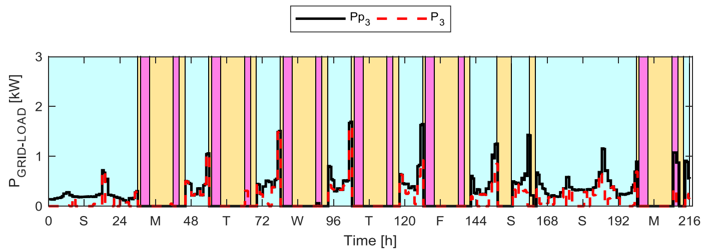


Fig. 4. Grid-power supplied to the residential load

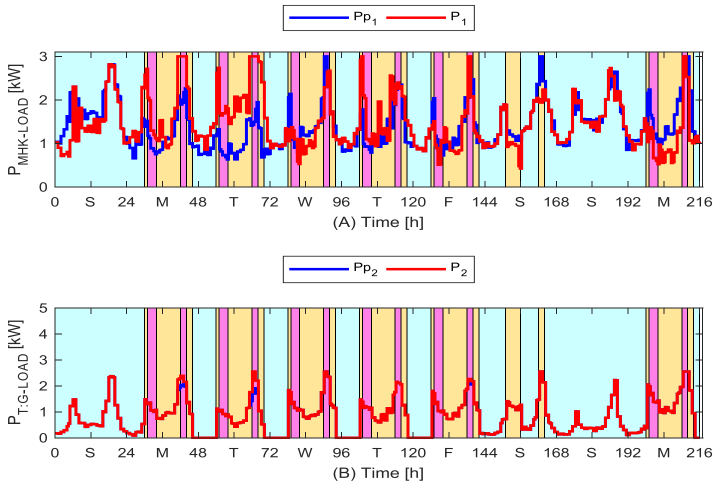


Fig. 5. RE system power supplied to the residential load

During the peak hours of the second Sunday, the actual load demand is less than the predicted one. Hence, this leads to excessive load power supply. As a result, the control algorithm allows the grid-to-load power to be reduced as a means of minimizing the electricity bills, as shown in Fig. 5. Hence, the renewable energy power is maintained constant.

For the simulated nine days, the predicted load demand resulted in an overall grid costs and energy sales revenue of ZAR40.34 and ZAR-64.90, respectively. After applying the rule-based control algorithm, the overall grid costs have decreased to ZAR28.15, while the overall energy sales revenue has decreased to ZAR-59.34. With reference to the baseline grid cost of the actual load demand, the newly acquired energy cost saving is 112% as compared to 110% yielded by the predicted load demand.

## 5. Conclusion

The developed rule-based control algorithm proved to handle the load demand uncertainty problem since the load was adequately met for the entire simulated 9 days. Whenever the excessive power has been supplied to the load, the grid-to-load power is reduced to minimize the electricity bills. Hence, the renewable energy penetration is maintained. Whenever there is a power shortage due to the predicted demand being less than the actual demand, the model proved to initially increase the RE power to mitigate the deficit. Therefore, grid-to-load power consumption is increased as a last option to supplement the deficit. This confirmed that the proposed algorithm benefits the user, by reliably and economically satisfying the load demand. Even though the baseline grid cost of the actual load demand is higher than the predicted one, the control algorithm yielded higher energy cost savings through reduced grid costs.

The results of this study have led to the future recommendation of applying rule-based control strategy under load shifting mechanism. Additionally, further study is needed to analyze the effect of the rule-based control algorithm of the payback period of the proposed grid-interactive system.

## Conflict of Interest

Authors declare no conflict of interest.

## Author Contributions

S. P. K developed the model and wrote the first draft of the paper. K.K. and T.M, both validated the model and contributed to the analysis of results. All authors contributed to the refining of the paper and had approved the final version.

## References

[1] Koko SP, Kusakana K, Vermaak HJ. Optimal energy management of a grid-connected micro-hydrokinetic with pumped hydro storage system. Journal of Energy Storage. 2017; 14:8-15.

[2] Samadi P, Mohsenian-Rad H, Wong VW, Schober R. Tackling the load uncertainty challenges for energy consumption scheduling in smart grid. IEEE Transactions on Smart Grid. 2013; 4(2):1007-16.

[3] Marais S, Kusakana K, Koko SP. "Techno-economic feasibility analysis of a grid-interactive solar PV system for South African residential load." 2019 International Conference on the Domestic Use of Energy (DUE). 2019; IEEE transcript: 163-168.

[4] Wang B. Intelligent control and power flow optimization of microgrid: energy management strategies (Doctoral dissertation, Compiègne).

[5] Xu Y, Xie L, Singh C. Optimal scheduling and operation of load aggregators with electric energy storage facing price and demand uncertainties. In2011 North American Power Symposium 2011; pp. 1-7. IEEE.

[6] Kong Z, Zou Y, Liu T. Implementation of real-time energy management strategy based on reinforcement learning for hybrid electric vehicles and simulation validation. PloS one. 2017; 12(7): 0180491.

[7] Luh PB, Michel LD, Friedland P, Guan C, Wang Y. Load forecasting and demand response. In IEEE PES General Meeting 2010 Jul 25 (pp. 1-3). IEEE.

[8] Kanwar A, Rodríguez DI, von Appen J, Braun M. A Comparative Study of Optimization-and Rule-Based Control for Microgrid Operation. Universitätsbibliothek Dortmund; 2015 Jan.

[9] Rezvan AT, Gharneh NS, Gharehpetian GB. Optimization of distributed generation capacities in buildings under uncertainty in load demand. Energy and Buildings. 2013; 57:58-64.

[10] Koko SP (2019). Optimal Energy Management Modeling Of A Grid-Connect Micro-Hydrokinetic With Pumped Hydro Storage (Doctoral thesis, Bloemfontein: Central University of Technology, Free State).

[11] Koko SP, Kusakana K, Vermaak HJ. Optimal power dispatch of a grid-interactive micro-hydrokinetic-pumped hydro storage system. Journal of Energy Storage. 2018;17:63-72.

[12] Vermaak HJ, Kusakana K, Koko SP. Status of micro-hydrokinetic river technology in rural applications: a review of literature. Renewable and Sustainable Energy Reviews. 2014; 29:625-33.

[13] Kusakana K., and Vermaak HJ. "Cost and performance evaluation of hydrokinetic-diesel hybrid systems." Energy procedia 61 (2014): 2439-2442.

[14] Koko SP, Kusakana K, Vermaak HJ. "Modelling and performance analysis of a micro-hydrokinetic river system as compared to wind system." In South African University Power and Energy conference (SAUPEC 2015), 2015; 141-147.

[15] Kusakana K. "Optimal operation control of a grid-connected photovoltaic-battery hybrid system." In 2016 IEEE PES PowerAfrica, pp. 239-244. IEEE, 2016.

[16] Kusakana K. "Optimization of the daily operation of a hydrokinetic–diesel hybrid system with pumped hydro storage." Energy Conversion and Management 106 (2015): 901-910.

[17] Koko SP, Kusakana K, Vermaak HJ. "Optimal Sizing of a Micro-Hydrokinetic Pumped-Hydro-Storage Hybrid System for Different Demand Sectors." Sustainable Cloud and Energy Services, 2018; 219-242. Springer, Cham.