

Harmonized Decision Modeling Process for Smart Grid Component Allocation

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ABSTRACT

This article presents a harmonized decision modeling framework for smart grid component allocation. The harmonized decision modeling process is intended to realize a decision support system for the smart grid system analysis. The traditional decision modeling processes have mainly stresses the economic feasibility of smart grid systems. However, the mathematical programming-based decision models for component allocation in smart grid systems are often designed without the enough consideration on the operational circumstances of component, and it reduces the utility of the solution. Our framework considers the operational circumstances of the system and the feasibility in terms of solving process for achieving a practical decision. As a case study, we present a component allocation of Phasor Measurement Units (PMUs) in smart grid systems. With the obtained results, the advantages gained from the harmonized decision modeling process are assessed and discussed.

1. INTRODUCTION

Recently, the smart grid has been proposed as an alternative modern power grid system [1, 2]. With various characteristics of the smart grid, the different perspectives of smart grid functions have been highlighted for extending the boundaries of the smart grid [3-5]. However, the realization of those functionalities causes complicated questions. Especially, as a prerequisite for the initiation of the smart grid, the allocation of smart grid components needs to be properly determined with the consideration of the actual functions of components in the system.

A primary role of the decision models for smart grid systems should be able to maximize the effectiveness of investment, by minimizing the cost for the optimal resource allocation in a given system. Based on the importance of the economic feasibility, there have been various topics of decision making for the optimal component allocation in the smart grid industry; however, there is a limited effort to realize the decision making framework, which can harmonize the physical and operational aspects of smart grid components. Due to the ruinous complexity of an exhaustive approach, each model has been designed separately based on its own assumptions without enough reflection of their functions. Although the functions of the smart grid significantly vary based on the definition of the smart grid systems and the scope of the investigation, several key functions that have higher priority and importance in the deployment of smart grid technologies are introduced – refereeing the reports from National Institute of Standard and Technology (NIST) [6] and Electrical Power Research Institute (EPRI) [7, 8].

This paper presents a harmonized decision modeling process that can be employed to realize a decision support system for the smart grid system analysis. This work is based on an idea that the component allocation strategy in smart grid systems should reflect the operational circumstances and should maintain the model hospitable for achieving a practical decision considering the functionality of smart grid systems. In this research, a PMU allocation case is used to describe the proposed processes and the IEEE 30 bus network is used to validate the work. In the next section, the exiting literature related to the decision making for the smart grid is presented. In Section 3, the harmonized decision modeling process is described. In Section 4, a component allocation is modeled and solved by using the harmonized decision model.

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2. LITERATURE REVIEW

For this literature review, four key functional areas (i.e., demand response, real-time wide-area situational awareness, distributed electric units, and distribution grid management) are selected based on the discussion in [6-9].

Demand response is a management strategy, which encourages energy consumption to control energy use in response to supply condition. This function also enables less expensive management to intelligently influence a load than the establishment of a new utility facility [10]. Bakker *et al.* [11] try to design the optimization methodology, which can incorporate communication between different technologies to reshape the energy demand profile. Due to much computational power required, their planning and control methodology is organized in a tree structure applying three steps of optimization levels. Mohsenian-Rad and Leon-Garcia [12] point out problems in utilization of the potential benefits of real-time pricing tariffs. They propose an optimal and automatic residential energy consumption scheduling framework for achieving a desired trade-off between minimizing the electricity payment and minimizing the waiting time for the operation of each appliance in household.

Real-time wide-area situational awareness plays a crucial role in smart grid as a measure for grid protection and control by providing time-synchronized data of power system operating states [13]. The information that system operators have influences on how effective a grid system's reaction will be against the contingencies. Zhu and Abur [14] describe the need for phasor measurements to overcome the limitation of conventional measurements. Authors show that by including redundant phasor information, errors in the parameters can be correctly identified. Aminifar *et al.* [15] present a model for the optimal placement of phasor measurement units (PMUs) considering contingency conditions (i.e., line outages and loss of measurements). Their work shows that integer programming can find the global optimality of PMU allocation problem with reasonable computational complexity.

The emergence of smart grid has stimulated the electric units to be distributed from one centralized spot [16]. This involves distributed generation unit, electricity storage, electric vehicles, and the qualitative improvement in demand side management. Bu *et al.* [17] present a distributed stochastic power generation unit commitment scheme by using hidden Markov models and a Markov-modulated Poisson process for modeling renewable energy resources and the power demand load, respectively. The effectiveness of their scheme is evaluated in terms of the cost of energy and pollutant emission through the simulation. Jia *et al.* [18] introduce the optimization process of the sizing and siting of electric vehicle charging stations. Their approach defines variables to represent the charging demand, and formulates the problem with a mixed integer quadratic programming with a graph theory.

Distribution grid management focuses on maximizing performance of electrical components of networked distribution systems and integrating them with transmission systems and customer operations [6]. Oshiro *et al.* [19] aims to perform voltage control in distribution system by the cooperative control between the interfaced inverter with distributed generation and the existing voltage control devices. In their work, a one-day schedule of voltage references for the control devices is determined by the optimization calculation. In [20], Soma *et al.* develop a model of Information and Communication Technology (ICT) system that considers the position of ICT infrastructure, and then propose a decision making process for finding the optimal allocation of WiMAX antennas with an active distribution network planning algorithm. In addition, Galli *et al.* [21] point that there was not enough efforts to give quantitative guidelines on how to choose one communication technology over the other in the design of smart grid. They analysed the role of power-line communications, and conducted electrical and topological analysis of the power distribution network.

3. HARMONIZED DECISION MODELING PROCESSES FOR SMART GRID COMPONENT ALLOCATION

EPRI initiated a discussion regarding the financial investment needed to create a viable smart grid. Through this report, expected components and estimated costs for the realization of the smart grid were introduced. It shows that the installation of components is an imperative task for the initiation of smart grid [7]. Although there could be various assumptions and conditions beyond this study that need to be taken into consideration, a basic equation which is generally used for the various components is formulated as Eq (1). As it shows, there are two main variables in installation of components, which are the cost per component and the number of components needed. Since the number of unit can be a variable that a decision maker can adjust based on the given condition (while the cost of component is assumed as a predetermined factor), the number of unit has been the subject of decision to be made in component allocation. Since there are thousands of possible types of components to be installed in smart grid systems, knowing how to deploy those components optimally is a crucial objective to be fulfilled by a smart grid analysis system.

$$C = \sum_{u \in U} (c_u \times n_u) \quad (1)$$

where, c_u = cost per component u , n_u = number of components u , and u = a component of set U which consists of necessary components for a viable smart grid.

Although Eq (1) explicitly shows that the number of unit is a crucial and controllable factor in resource allocation, excessive concentration on reducing the number of units to be installed can lead to an impractical decision. Since the purpose of the traditional decision making has been the minimization of the amount of financial investment while ensuring the normal and stable operations of a given system, the traditional processes have mainly stressed the aspect of economic feasibility rather than the considerations on the substantive operational aspects. However, the more suitable decision model process has to animate the model by incorporating the operational aspect of system. Specifically, the decision model should include the considerations on the functionality of component for enhancing the utility of solution, as well as the economic feasibility by minimizing cost. Feasibility of the model needs to be reinforced and confirmed by a decision maker for embracing the variability in operation of system.

Due to the complexity of smart grid system, it is neither an extemporary nor a simple task to find a generalized methodology that can define the model structure applied in smart grid context. In this article, we propose a general decision modeling process for smart grid component allocation as shown in Figure 1.

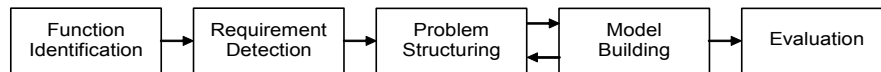


Figure 1. Harmonized decision modeling process.

When applying this decision modeling process in the smart grid context, a decision maker needs to identify the functions, which are expected as results of the installation and operation of the component in a given grid system. Since the complexity in function identification (e.g., an entanglement between functionalities over multiple domains) is frequently arisen, this step encourages a decision maker to conduct the exhaustive review on the functional effects of the component.

While the step of function identification is for sketching a rough outline of decision to be made, the requirement detection process requires the decision maker to study the problem with various angles and depths for defining important points to be handled through the model. The requirements discovered in this process are the requirements of system, which is directly related to the realization of elemental operation, and also the decision requirements, which should involve the circumstantial consideration.

The problem structuring is the next step, and a focused way of thinking [22] for solving the problem given by the function and the system requirement. Problem structuring can be conducted with identification of several parts of a problem, such as goals, variables, parameters, constraints, and possible uncertainties [23]. The model building is very dynamic process interacting with the problem structuring. Particularly, the feasibility of model must be considered in this process. In contrast with the prior processes that specialize the decision model based on the functions and requirements discovered, the model building process must accord flexibility to the model, so that it can tolerate the inherent complexity of the problem and the variability in the operational application. After the solving process according to the harmonized decision modeling, the results need to be evaluated by the stakeholder.

4. PHASOR MEASUREMENT UNIT ALLOCATION WITH HARMONIZED DECISION MODELING

In the respect of system reliability and security, the operation of stable monitoring system is a fundamental prerequisite. As an effort for pursuing the sound measurement and estimation of state of electricity delivery, the technology of Phasor Measurement Unit (PMU) has been developed over the past few decades [24] and now it is a leading candidate of electrical performance measurement technology [14]. One of the critical issues in utilizing PMUs has been the optimal PMU allocation. In this section, the PMU allocation is chosen as a representative component allocation task, and the modeling process complying with the harmonized decision modeling process is applied.

Although there has been a noticeable research works dealing with the PMU allocation [25], those research works have mainly focuses on the minimization of number of PMUs to be placed in a given system. As a result, PMU allocation has been apt to simply reduce the number of PMU, rather than to consider the harmonization of model with the environment of the region where PMUs will function and with the variability of system operation. Based on the proposed sequence of decision modeling methodology, PMU placement problem can be restructured.

The primary function that a decision maker or stakeholder in a business of PMU operation could anticipate is the electrical state measurement for determining the health of the electricity grid system. Based on this primary function,

several derived functions can also be discovered (e.g., prevention of power outage, load control including the load shedding, and increase in power quality).

Now the requirements for achieving those functions need to be detected in the decision modeling. The configuration of PMUs should observe buses as many as possible, in order to effectively actualize the primary function, which is to allow a system operator to determine the health condition of electricity grid system. Since the level of observation, which indicates how many buses can be observed by the set of PMUs is decided by the configuration of PMUs, a decision maker needs to understand the observation rule acting in PMU network. The rules used in this paper are listed below and the first two rules are adapted from [26].

- Rule 1: Installation of a PMU in a given bus makes itself and other buses incident to that bus observable. This implies that the voltage phasors of these buses are known.
- Rule 2: If only one bus is unobservable among a zero-injection bus and its entire incident buses, it can be observable using the Kirchhoff's current law (KCL) at the zero-injection bus.

In addition, one additional rule (according to [27]) is applied in this paper to minimize the number of PMU by avoiding the overlap of observability caused by multiple zero-injection buses.

- Rule 3: If a bus is connected to two or more zero-injection buses, there is no need for the bus to be observed by all of the connected zero-injection buses.

In addition to the primary function, the examination considering the subsidiary functionalities of the component encourages a decision maker to expand the boundary of idea on requirement detection. As stated above, three concrete functions can be taken into account, that are *prevention of power outage*, *load control including load shedding*, and *the increase in power quality*. First, real-time monitoring can detect the fault in the energy grid system, and suppress the wide spread of power outage. Since the impact of power outage varies depending on the situation where it occurs, it is important to consider the factor that could affect the significance of impact. The power outage impact can be determined by considering the population that will be affected by a fault of a certain substation or lines linked to the substation, the significance of electrical facilities operated by substations, and the presence of interregional area in each region. For instance, the region that has more population would have greater importance than other regions in terms of the importance of prevention of power outage. And the region that has a governmental agency highly relies on the computer systems utilizing critical data would have to receive more significant attention than other regions. If a region is acting as an interregional gate where connects two different regions, more considerations need to be located on that region. Also, a load control is a noticeable function that would be performed by the utilization of PMU. When the load control function is considered, the amount of electricity consumed in a specific region will come into the spotlight due to the high possibility of the high demand region to be in need of the load control. As the last additional function, the increase in power quality is expected to be dealt with in the PMU allocation. This function attracts the entity that is sensitive to the quality of electricity. For example, to manufacturers producing subminiature devices (e.g., semiconductor chips), even a minimal change in electrical performance can seriously affect their productivity and the quality of products. The requirements listed here are particularly meaningful in the demand side aspect, while other aspects also exist: that are system interconnection, generator and line modeling, renewable integration, and congested area requiring online monitoring. However, this paper focuses on the five selected requirements preferentially. The other requirements will be considered in future research.

In the problem structuring, the requirements are entered in the model as objectives. To earn the technical margin of modeling for further applicable operations, the design of model focuses on efficient solving process. Although the determination of the significance of each factor through the systematic calculation is required, this calculation is beyond the scope of this research. Thus, in this paper it is assumed that the valid calculation for each factor of each region is done by a statistical decision support tool.

As a whole, there are six objectives in this PMU allocation considering smart grid system context: 1) minimization of the number of PMUs to be installed; 2) maximization of population, which is supplied by substations observed by PMUs; 3) maximization of significance of facilities in regions, which are supplied by substations observed by PMUs; 4) maximization of level of observation for interregional area; 5) maximization of amount of electricity demand of regions, which are supplied by substations observed by PMUs; and 6) maximization of the number of facility sensitive to the quality of electricity in regions observed by PMUs. Based on them, a multi-objective problem having six objectives can be:

$$\min F_1(x_i), \max F_2(x_i), \max F_3(x_i), \max F_4(x_i), \max F_5(x_i), \max F_6(x_i), \text{ subject to } x_i \in S \quad (2)$$

where S is the set of feasible solutions in which $x_i = 1$, if a PMU is placed at bus i , otherwise $x_i = 0$, for all $i \in \{1, 2, \dots, n\}$, and n is the number of buses in a given system.

Apparently, this is a complex problem, which involves six different objectives, and it would be very hard for these objectives to harmonize each other. In other words, these multi-objectives would be excessively competitive each other, which could lead to the invalid solution. It means that the best PMU allocation for the one objective may not be the best for the other objectives. Also, when it is recalled that the original PMU allocation has been a large-scale combinatorial optimization problem, which finds the solution of Eq (3) [28], to solve a hexa-objective combinatorial problem having two factors, number of PMU (N_{PMU}) and placement set $S(N_{PMU})$, becomes a formidable task.

$$\min_{N_{PMU}} \{ \max R_T(N_{PMU}, S(N_{PMU})) \} \quad (3)$$

As a way to allow the tolerance to the model for solving process, the previous models need to be remodeled. By remodeling Eq (3) to Eq (4), PMU allocation problem can be solved with deterministic approach.

$$\min \left(\sum_{i=1}^N x_i \right) + \max \left(\sum_{i=1}^N r_i \right), \text{ subject to } r_i \geq 0 \quad (4)$$

where r_i is the redundancy of observation of bus i by PMUs.

Now this bi-objective programming is remodeled by involving the considerations on functionality and requirements of smart grid utilizing PMU. The minimization of number of PMUs to be installed (i.e., $\min F_1(x_i)$) is regarded as a primary objective of PMU allocation and the other five objectives in Eq (5), which is related to the requirement of harmonized modeling, are expressed as a function of redundancy. There are two distinctive features in this formulation. It uses the weighted sum method, which utilizes a priori articulation of preferences, one of the main methods solving multi-objective optimization, and it integrates all different parameters into the model as a function of redundancy, so that the model can be used in various applicable circumstances of operation and also can retain the computational margin in solving process. Eqs (6-1) to (6-5) (in Table 1) show a set of model, which is generated from the harmonized decision modeling process for PMU allocation in smart grid context.

$$\begin{aligned} & \min \left[\sum_{i=1}^N x_i - \{ F_2(r_i) + F_3(r_i) + F_4(r_i) + F_5(r_i) + F_6(r_i) \} \right] \\ & = \min \left[\sum_{i=1}^N x_i - \sum_{i=1}^N \left(\frac{w_1 p_i r_i}{\sum_{i=1}^N p_i} + \frac{w_2 s_i r_i}{\sum_{i=1}^N s_i} + \frac{w_3 t_i r_i}{\sum_{i=1}^N t_i} + \frac{w_4 d_i r_i}{\sum_{i=1}^N d_i} + \frac{w_5 e_i r_i}{\sum_{i=1}^N e_i} \right) \right] \\ & = \min \left[\sum_{i=1}^N x_i - \sum_{i=1}^N \left\{ \left(\frac{w_1 p_i}{\sum_{i=1}^N p_i} + \frac{w_2 s_i}{\sum_{i=1}^N s_i} + \frac{w_3 t_i}{\sum_{i=1}^N t_i} + \frac{w_4 d_i}{\sum_{i=1}^N d_i} + \frac{w_5 e_i}{\sum_{i=1}^N e_i} \right) (r_i^1 + r_i^2) \right\} \right], \text{ subject to } r_i \geq 0 \end{aligned} \quad (5)$$

where, p_i = population of regions where bus i supplies electricity, s_i = significance of facilities in regions where bus i supplies electricity, t_i = index of interregional area, d_i = electrical demand of regions where bus i supplies electricity, e_i = level of sensitivity of facilities in regions, where bus i supplies electricity, and w_1, w_2, w_3, w_4 and w_5 = weights for p_i, s_i, t_i, d_i , and e_i , respectively. Each parameter in the objective function of redundancy is normalized by dividing it by sum of parameters of all buses. Weight function w_i implies the level of importance which a decision maker attributes.

As a case study, IEEE 30 bus system is chosen and solved by using a mathematical model devised from harmonized decision modeling process. An artificially made data set is also utilized in this problem as seen in Table 2. The population, and electrical demand are randomly generated integral values within $p_i(\text{people}) \in [5,000, 500,000]$, and $d_i(\text{kWh}) = p_i u$ where $u(\text{kWh}) \in [25, 50]$. The ranges of three integral indices are presupposed as $s_i \in [0, 5]$, $t_i \in [0, 2]$, and $e_i \in [0, 2]$, respectively.

Table 1. PMU allocation model generated from the harmonized decision modeling process.

Constraints	Description
$a_{ij} = \begin{cases} 1, & \text{if } i = j \\ 1, & \text{if bus } i \text{ and } j \text{ are connected,} \\ 0, & \text{otherwise} \end{cases} \quad (6-1)$	<p>N: the total number of buses of a given system I: a set of buses in a given energy grid system I_{ZIN}: a set of buses which are zero-injection buses or which are connected with zero-injection buses I_{NZIN}: a set of buses which are not related with zero-injection buses O: a set of buses which only have overlapped zero-injection buses as incident buses O_j: a set of incident zero-injection buses of j in O. For making the formulation preventing the overlap between zero-injection networks, variable $g_{i,j}$ is designed. Redundancy variable r_i is divided into two subordinate variables which are redundancy from the rule 1 (r_i^1) and redundancy from the rule 2 (r_i^2). (6-1): a_{ij} indicates connectivity between buses, x_i variable indicates PMU placement at bus i, and f_i is an indicator variable representing the observability of bus i. (6-2 and 3) corresponds to the observability rule 1 and 2 for buses in zero-injection network (6-2) and for buses not in zero-injection network (6-3). (6-4) corresponds to the observability rule 3. If a bus is overlapped by two zero-injection networks, it is not required to consider both of zero-injection networks. (6-5) calculates total redundancy over a given system, which is to be maximized.</p>
$x_i = \begin{cases} 1, & \text{if PMU at bus } i \\ 0, & \text{otherwise} \end{cases}, \text{ and } f_i = \begin{cases} 1, & \text{if bus } i \text{ is observable} \\ 0, & \text{otherwise} \end{cases}, \quad \forall i \in I$	
<p>For buses in zero-injection network,</p> $\sum_{j=1}^N a_{ij} x_j - \left(\sum_{j=1}^N a_{ij} \right) f_i \leq 0, \text{ and } \sum_{j=1}^N a_{ij} x_j - f_i \geq 0, \quad \forall i \in I_{ZIN}. \quad (6-2)$	
<p>For buses not in zero-injection network,</p> $\sum_{j=1}^N a_{ij} x_j - \left(\sum_{j=1}^N a_{ij} \right) f_i \leq 0, \text{ and } \sum_{j=1}^N a_{ij} x_j \geq 1, \quad \forall i \in I_{NZIN}. \quad (6-3)$	
<p>For overlap prevention,</p> $\sum_{j=1}^N a_{ij} f_j \geq \sum_{j=1}^N a_{ij} - 1 + \sum_{j \in O_j} g_{i,j}, \quad \forall i \in I_{ZIB} \quad (6-4)$ $\sum_{i \in O_j} g_{i,j} \geq 1, \quad \forall j \in O$ <p>and $g_{i,j} \geq f_j, \quad \forall i \in O_j, \forall j \in O$.</p>	
<p>For redundancy calculation,</p> $r_i^1 = \sum_{j=1}^N a_{ij} x_j, \quad \forall i \in I$ $r_i^2 + \sum_{j=1}^N a_{ij} x_j \geq 1, \quad \forall i \in I \quad (6-5)$ <p>and $\sum_{j=1}^N a_{ij} x_j - \left(\sum_{j=1}^N a_{ij} \right) (r_i^2 - 1) \leq 0$.</p>	

Table 2. Randomly generated parameters for IEEE 30 bus system.

bus	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
p	84	52	496	124	372	130	203	320	329	163	475	53	337	29	48
s	2	2	4	4	3	5	3	2	4	2	2	0	1	1	3
t	0	2	1	2	1	2	2	1	0	2	2	1	0	1	1
d	24	22	218	38	174	61	63	144	161	54	143	17	88	13	23
e	0	0	1	1	0	0	1	1	0	0	2	2	0	0	0
bus	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
p	498	22	367	431	494	9	9	486	226	174	128	89	362	245	492
s	3	0	4	1	1	3	2	4	2	3	2	2	4	4	0
t	2	0	2	0	0	1	1	2	2	1	2	1	0	2	1
d	144	7	184	112	158	2	3	146	61	47	45	40	105	113	187
e	0	2	2	1	2	1	2	1	0	0	0	2	1	0	2

$p=10^3$ people (population), $d=10^5$ Wh (daily energy consumption)

Figure 2 shows the different optimal PMU allocations based on the different angles of modeling approach. In this study, GAMS (General Algebraic Modeling System) software and a solver, CBC (COIN-OR Branch and Cut), are used to solve this optimization problem. First diagram indicates the optimal PMU allocation point when this problem is dealt with as a mere location selection problem based on the network configuration, and bus 2, 4, 10, 12, 15, 18, and 27 are chosen to have PMUs. Second and third diagrams show the optimal PMU allocation, which are solved by the

harmonized decision model. The different intention, i.e., weight, of the decision maker, as well as the utilization of harmonized models could affect the component allocation strategy, 29% and 43% of disparity in allocation, respectively. This result explicitly describes that the component allocation problem should incorporate the considerations on the operation condition of component with the perspective of smart grid functioning.

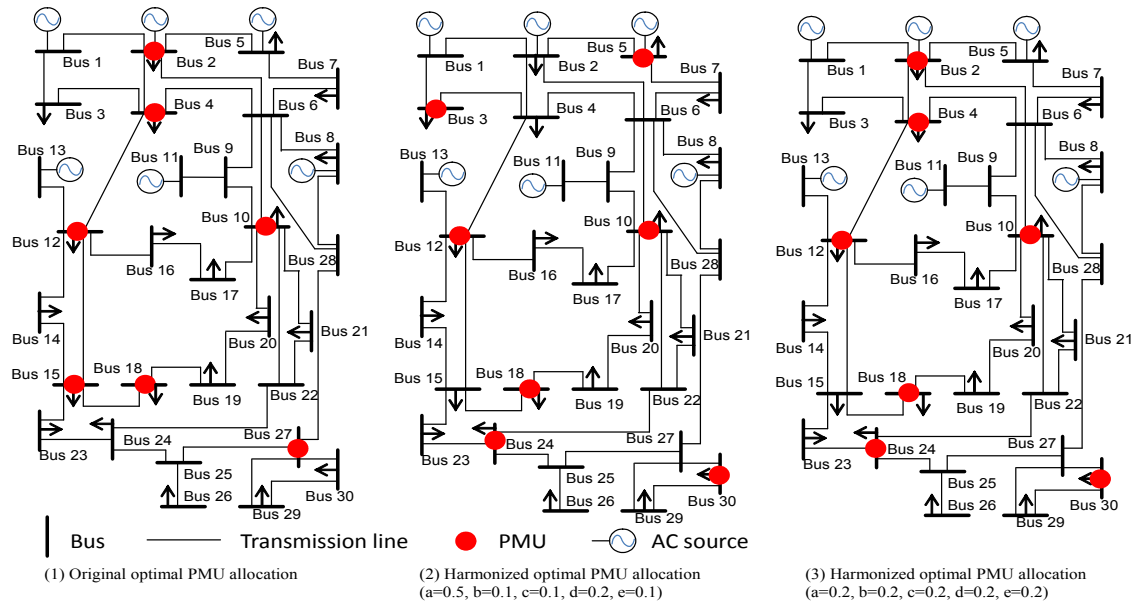


Figure 2. Optimal PMU allocations for IEEE 30 bus system according to different operation circumstances.

When different kinds of solvers solve this model, it is checked that the solutions can vary depending on solvers' own solving mechanisms. For instance, SCIP (Solving Constraint Integer Programs) gives 2,4,10,12,15,18, and 27 as an optimal location set of PMUs for the third case ($a=b=c=d=e=0.2$), having 29% of disparity in PMU location compared to CBC solver. It indicates that this harmonized PMU allocation programming still has complexity remained, which needs to be alleviated through further research.

5. CONCLUSION

This paper proposed a harmonized decision model process with the aim of involvement of operational condition in decision modeling. We intended to consider the requirements both of system and decision model for achieving the functionality of component in the smart grid context. The management tools need to be optimized corresponding to the system and the smart grid requires a decision, which can incorporate and harmonize the technologies with a given energy grid circumstance for realizing an intelligent two-way electricity flow. In this study, the modeling methodology was addressed for efficient solving process for the PMU allocation. For avoiding the ruinous complexity of decision problem, a hexa-objective optimization problem was converted to a bi-objective problem by expressing the objectives as a function of a main variable (i.e., redundancy). The results of applying the proposed method to the PMU allocation showed that harmonized decision modeling approach can provide a decision maker a new strategy of component allocation. Although the evaluation on validity of factors and weight in calculation was not thoroughly investigated yet, this work can be a foundational discussion regarding the essential concept of the harmonized decision model process. As a future work, the distributed renewable generation deserves considerable attention in terms of grid management, because it causes various types of interconnection between components. Also the quantification and normalization of dissimilar factors could be a huge range of investigation in itself. We will continue to investigate these aspects with the harmonized decision model process. Finally, an in-depth study on the novel optimization methodologies, which could solve the formidable multi-objective problem effectively with smart grid setting, is a promising research area.

ACKNOWLEDGEMENTS

This research is supported by the NSF I/UCRC for e-Design.

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