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Context-Aware Self-Organized Resource Allocation In Intelligent Water Informatics

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CONTEXT-AWARE SELF-ORGANIZED RESOURCE ALLOCATION IN INTELLIGENT WATER INFORMATICS

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In this paper, we investigate the water resource allocation for smart water grids (SWG) with users' context information. A water resource sharing scheme is proposed for efficient managing water resources with the aid of the intelligent water informatics. A novel spectral clustering algorithm is developed to classify end-users into different communities with respect to the end-users' profiles. We characterize the dynamics of the SWG with the Markov decision process (MDP), and an online Q-learning aided water allocation algorithm is conceived by virtue of the MDP for adapting the dynamics of the SWG, thus improving the water utility efficiency. Numerical results demonstrate the advantages of the proposed scheme over the conventional static schemes.

I. INTRODUCTION

Severely aging infrastructure of water grid always leads to water loss, water theft as well as the loss in revenue of water utilities [1]. In order to improve the efficiency of the water resource distribution, the smart water grid (SWG) has emerged as a highly efficient next-generation water management system, which relies on the advanced information and communication technologies to overcome the problems of the traditional water resource management systems [2]. With a combination of communication technologies and water resource management systems, SWG helps ease the regional and/or temporal imbalance of water resources by accurately controlling water demand and supply in real-time. In addition, Endowing SWG with self-organizing capabilities is instrumental in helping operators perform smart operations and maintenance.

Inherently, the accurate control and operation of the water distribution relies on the context information of the SWG, which generally demands the real-time two-way information transmission, namely management-center collecting information from end-users (e.g., meters deployed at factory, farmland, residents etc.) as well as it disseminating signaling information to end-users. Specifically, the reliability as well as the real-time requirement of information are crucial for efficient delivery of water resources from the water generating units to end-users [3]. The detrimental impact of equipment failures, capacity constraints, and unrespectable reduction of qualities of water resources, which cause the unbalance of water resources allocation, will be largely minimized by the effective water condition monitoring, diagnostics and optimization [4]. The intelligent water monitoring and control enabled by context information and communication technologies [5] have become essential to realize the envisioned SWG.

A wireless sensor networks based water-grid structure was investigated in [6], where the small sensors are able to promptly detect particular events or working conditions and then to report related information to the water manage system. In [7], the smart wireless sensor system was currently deployed in water management systems to keep track of the information of the end user's water consuming activities, preferences as well as locations and time. However, most of the current approaches cannot meet the requirement of real-time water supply for end-users. With the aid of contextual information such as end users' water consuming preferences, water qualities and the state of the grid network, the water allocation system is able to deliver more suitable water to end-users in real time. In traditional systems, the water allocation cannot coincide with the dynamic quality of water service (QoWS) requirements, which is natural in real situations. To the best of our knowledge, few literatures has ever addressed on the systematic research results of SWG by optimizing the water resource allocation with the aid of the context information of SWG.

The transmission of the context information of SWG demands an efficient communication network. Typically, mesh networking together with sensor nodes is a cost effective approach with respect to its dynamic self-organization, self-healing, as well as self-configuration and high scalability services [7]. Note that the advanced water metering infrastructures and information management systems are the main sources of context information.

Reinforcement learning (RL) approach describes a learning scenario, where an agent gradually improves its behavior by taking optimal actions in its environment with the reward for performing well or under the punishment for failure [8]. The Q-learning, a good RL approach to realize self-organization function allows the agent to build incrementally a Q-function, which attempts to estimate the discounted future costs while taking an action in the agent's current state. The output of the Q-function is called Q-value. By exploring the water grid environment, the agents (water consumer community) create a table of Q-values for both states of the context and potential actions of water allocation.

In this paper, we conceive a context-aware dynamic water resource allocation scheme for SWGs. A generic intelligent water distribution framework is designed with the combination of the information/communiction technologies and water grid. A novel spectral clustering algorithm is developed to classify end-users into different communities with respect to the end-users' profiles. The Markov decision process (MDP) is employed to characterize the dynamics of the SWG, and then an online Q-learning aided water allocation algorithm is developed for adapting the dynamics of the SWG.

Figure 1: Schematic diagram of SWG

II. CONTEXT AWARE SWG MODEL

A generic SWG system is illustrated in Fig. 1, where the SWG is designed and operated with the following functions: to make good use of water resources including rainwater, reclaimed water and seawater; to distribute, manage and transport water efficiently to ease the imbalance of water resources; to monitor the stability of SWG in real time by virtue of an advanced sensor network [3]. In the currently existing water resource management systems, there is a large amount of water loss owing to frequent water leakage. Furthermore, the utilization of water resource is under a low efficiency and as well under a bad end-user's experience owing to the fact that the diversity of the end-users' QoWS requirements is seldom concerned. Naturally, different end-users in SWGs have different interests for water resources, namely different QoWS requirements. In addition, manual operations in SWG would be very costly. Therefore, the self-organizing functions of the water-resource management are endowed to adapt the dynamics of SWG, which include the change of the supply of water resources, the varying of users' interests, as well as the change of the operation scheduling/planing of SWG, etc.

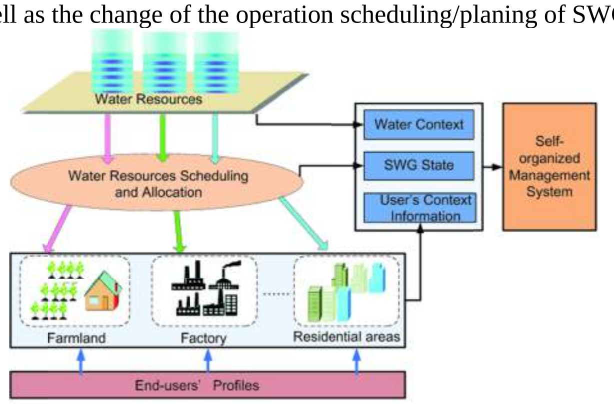

Figure 2: Framework of self-organized management system in SWG.

Fig. 2 illustrates a typical water resource management framework, which consists of water resources module, self-organized management module and end-users module. Different types of water resources such as rainwater, reclaimed water and seawater are associated with the water resource modules, which are typically deployed at the edge of the SWG. The end-users module represents the water consumers such as residents, industry and farmland and so on, which are clustered into different 'water communities' by considering the similar water consuming profiles of the end-users, e.g., the habit of water usage, the location of end-users, the water consuming QoWSs and quantities, etc. In this contribution, the user's context information includes the information of the user required QoWSs and the water volume of the really-depleted. The optimal and dynamic water resource allocation is performed by the self-organized management module based on the information of users' context, the resources' context, as well as the SWG network states. Besides the measuring functions, the deployed smart water meters have the communication and control functions, that is they may collect/report the information (may be collected by sensor network) to the management center, and as well they may control/adjust the water supply upon receiving the instructions from the management center. We list the notations in TABLE I.

Table 1 Notations

Notation	**Description**
X	Set of water communities
Θ	Set of water QoWS
Γ	Set of water resource types
Ω	Set of water resource context information, e.g., the costs of production and/or storage
N	Set of SWG state information, e.g., the costs of operation/maintenance of pipeline networks
$\Phi_{c,g}$	Volume of resource g distributed to community c
$\Psi_{c,g}$	Volume of resource g really-depleted by community c

III. PROBLEM FORMULATION

In this section, we shall formulate the problem of water resource allocation. We denote $\Gamma = \{g(c), \forall c \in \mathrm{X}\}$ with $g(c)$ being the favorite water types of community c. And, $\Theta = \{q(c,g), \forall (c,g) \in (\mathrm{X},\Gamma)\}$ with $q(c,g)$ being the QoWS level that SWG provides water type g to community c. Note that each type of water resources has been tagged with a specified QoWS. In addition, each community may expect to consume multiple types of water resources simultaneously, that is each community has diverse QoWS requirements in one time. W.o.l.g, we assume that the action of the water resource allocation is updated in time-slots. In the end of a time-slot t, the data of the depleted volume $\Psi_{c,g}^{t}, \forall(c,g)$, which is measured by the water meters, will be reported to the management center. Since the data of the allocated volume $\{\Phi_{c,g}^{t}\}$ at time-slot t is inherently known at the center, the difference of these two volumes can be directly computed as $\Delta_{c,g}^{t} = |\Phi_{c,g}^{t} - \Psi_{c,g}^{t}|$. In this contribution, are termed as the users' context information and insightfully, they denote the weights of the links between multiple resources and multiple communities in a bipartite graph. We further assume that the operator has configured the buffering water-pools for each community for leveraging the dynamics of the water arrivals, which typically leads to additional costs. Therefore, we expect the really-consumed volume and the allocated volume could be matched as better as possible, even under the dynamics of both the water-resource supply and pipeline networks. Considering the system utility in a long time horizon, we define the averaged water allocation mismatch as the objective function, which is expressed as

$$\mathrm{E}\{\Delta_{c,g}^{t}\} = \limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T}\Delta_{c,g}^{t}(w^{t}, n^{t})\; w^{t} \in \Omega, n^{t} \in \mathrm{N}, \forall(c,g). \quad (1)$$

Our objective is to minimize the mismatch by allocating different types of water resources for the end-users under the constraint of QoWS with respect to the dynamics of the SWG.

$$\min_{\Phi_{c,g}^{t}\geq 0} \sum_{c\in \mathrm{X}}\sum_{g\in\Gamma}\lambda_{c,g}\mathrm{E}\{\Delta_{c,g}^{t}\}, \quad (2)$$

$$s.t. \mathrm{E}\{\Psi_{c,g}\} \leq \mathrm{E}\{\Phi_{c,g}^{t}\}, \forall(c,g), \quad (3)$$

$$q(c,g) \in \Theta, \forall(c,g) \in (\mathrm{X},\Gamma), \quad (4)$$

where $\lambda_{c,g}$ denotes the corresponding weight, Eq. (3) constraints that the averaged depleted volume cannot exceed the allocated volume, and Eq. (4) ensures to satisfy the QoWS requirements.

The solving of this problem is to find the optimal matching between multiple water resources and multiple water communities in a long-time horizon. Generally, the end-users are located in a very broad area. Hence, even some of them have the same profile and then could be clustered into one community, the number of communities is typically very large. This requires an efficient approach of community-clustering. Furthermore, the solution of the problem should be adapt to the dynamics of the SWG, which typically involves in the highly-dimensional information, an online learning aided dimension-reduced dynamic programming approach is demanded herein. In a word, the management system should be self-organized to perform the optimal water allocation or the autonomic operation/maintenance with respect to the varying of different types of information.

IV. PROPOSED WATER RESOURCES ALLOCATION SCHEME

In this section, the optimal water resource allocation is determined with the aid of context information, while satisfying the QoWS of water communities.

A. Clustering Communities

The end-users are clustered into different communities based on the profiles of the end-users, which include the water utilization habit, the geographic location of users, the water volume and/or QoWS required by end-users. A spectral clustering algorithm is developed with the aid of spectral graph theory, which has the advantage of clustering in the sample space of arbitrary shape and shows good convergence to the global optimal solution [9]. Our novel spectral clustering method for clustering water communities is realized through constructing adjacent matrix and gain matrix (c.f. [9]). We assume that the SWG consists of N end-users, which are classified into $K = || \mathrm{X} ||$ water communities. The calculation of the two matrices is given as follows:

• **Adjacent Matrix**: Let denote A as the adjacent matrix in the network ($A : N \times N$). If there is a connection between user i and j, which represents a common profile or interest, then it marked as $A_{ij} = 1$, else $A_{ij} = 0$. Further defining the mutual matrix M, the element of M can be expressed as: $M_{ij} = \sum_{k=1}^{N} A_{ik} A_{kj}$, where A_{ij} and A_{kj} are the elements of adjacent matrix A, and furthermore $A_{ik}A_{kj} = 1$ when user i and user j are both have a connection side with user k, which represents the number of common neighborhoods (common interests) between user i and user j.

• **Gain Matrix**: Let define l_i and l_j as the connection degrees of user i and user j respectively, which denote the numbers of the connections between the specified user and other users in the network. And further define the number of common neighborhoods between random users pairs (i, j) as $\frac{l_i l_j}{N}$. We compute the gain function as:

$E = \sum_{ij} (M_{ij} - \frac{l_i l_j}{N}) \Delta_{ij}$, where Δ_{ij} denotes the membership function in the community. If user i and j are in the same community, $\Delta_{ij} = 1$; else, $\Delta_{ij} = 0$. Concretely, E can be interpreted as the difference between the numbers of common neighborhood based on common interests and that based on random selection. Then, we denote the mark vector of the community as $S = (s_1, s_2 \ldots s_N)$. If user i belongs to the first community, $s_i = +1$, else $s_i = -1$. We obtain that $\frac{1}{2}(s_i s_j + 1) = \Delta_{ij}$, and then

$E = \frac{1}{2} \sum_{ij} (M_{ij} - \frac{l_i l_j}{N})(s_i s_j + 1)$. It can be expanded as

$$E = \frac{1}{2} \sum_{ij} (M_{ij} - \frac{l_i l_j}{N}) s_i s_j + \frac{1}{2} \sum_{ij} (M_{ij} - \frac{l_i l_j}{N}), \qquad (5)$$

We only consider the contiguous item for the communities, namely the former item, as

$$\frac{1}{2} \sum_{ij} (M_{ij} - \frac{l_i l_j}{N}) s_i s_j = \frac{1}{2} \sum_{ij} (\sum_{k=1}^{N} A_{ik} A_{kj} - \frac{l_i l_j}{N})_{N \times N}, \qquad (6)$$

Finally, the gain matrix C can be computed as $C = (c_{ij})_{N \times N} = (\sum_{k=1}^{N} A_{ik} A_{kj} - \frac{d_i d_j}{N})_{N \times N}$. Given the adjacent matrix A and the gain matrix C, the complicated network is firstly clustered into two communities: calculate the principal eigenvectors of the largest eigenvalue of the gain matrix C, and cluster the SWG network into two water communities based on the symbols of the main elements in the eigenvectors. Continuously performing the same process with this spectral clustering method, each community may be divided into different smaller-sized communities. The clustering process stops while deviating the specified conditions.

B. Q-Learning Aided Dynamic Resource Allocation

In this section, the Q-learning aided self-organized algorithm is developed for water resource allocation. After the agent makes a decision based on the current state of the context environment, it receives the profit, either in positive or negative. If the profit of an action is positive, the probability of this action being selected again is increased, otherwise it decreases.

Considering that the resource context information $w^t \in \Omega$ and the SWG state information $n^t \in \mathrm{N}$ are varying between different water allocation time-slots, we may portray the solving of problem Eq.(2) with an MDP approach. Let rewrite the constrained problem Eq. (2) into an unconstrained MDP problem by virtue of the Lagrange approach. We finally obtain the corresponding value functions $\{V(f)\}$ with respect to states $\{f\}$.

WLOG., upon selection of an action, the agent should analyze the new state that it has transited to. Mathematically, the probability of transition to state f, starting from state h can be expressed as $P(H_t = f | H_{t-1} = h, a_{t-1}) = P_{hf}(a_{t-1})$, where a_{t-1} is the action taken at time instance $t-1$ corresponding to H_{t-1}, the previous state.

Since the agent has no means of knowing if one action selected was good or not, a reward is required to leverage the measurement. A positive reward signifies a beneficial action, while the negative says that it requires to further try other potential actions. While considering the long-term reward, the value function can be formulated by the Bellman function:

$$V^{\pi}(f) = R(\pi(f)) + \gamma \sum_{h} P_{hf}(\pi) V^{\pi}(h) \tag{7}$$

where $V^{\pi}(f)$ is the value function in state f with policy π, γ is the discount factor, and $R(\pi(f))$ is the immediate reward, which has larger weight than future rewards achieved when transiting to the future state h.

The goal of RL is to find an optimal policy π^*, which maximizes the total discounted payoff V^*:

$$V^*(h) = \max\, [R(h,a) + \gamma \sum_{y} P_{fh}(a) V^*(f)]\,. \tag{8}$$

The solving of the above problem requires the knowledge of the transition probabilities, which are naturally unknown a prior. The mapping from states to actions can be achieved over an infinite horizon of states and actions with the help of the Q-values. For each of the mapping, it associated with a Q-value:

$$Q^{\pi}(h,a) = R_h(a) + \gamma \sum_{f} P_{fh}(\pi(h)) Q^{\pi}(f)]\,. \tag{9}$$

Given an optimal policy, the Q-values associated with Q^* are also maximized. Determining the optimal policy is thus closely related to the determining of the optimal Q-values. This can be realized at the agent through a recursive learning procedure.

$$Q(h,a) = Q(f,a) + \partial[R + \gamma \max_{a'} Q(f,a') - Q(h,a)] \tag{10}$$

where ∂ is the learning rate and a is the selected action, which has caused the transition from the initial state h to the new state f.

The states that the agents use to characterize the environment are given by $I_{cg}, QoWS_{cg}$ and UCA_{cg}:

$$QoWS_{cg}=\begin{cases}1, & \text{above threshold} \\ 0, & \text{else}\end{cases}, \quad I_{cg}=\begin{cases}1, & \text{for coverage} \\ 0, & \text{no coverage}\end{cases} \tag{11}$$

$$UCA_{cg}=\begin{cases}1, & high \\ 2, & meduim \\ 3, & low\end{cases} \tag{12}$$

where I_{cg} is a binary indicator of the resource coverage on the water communities (0 for no coverage, 1 for coverage), $QoWS_{cg}$ is a binary value illustrating if the water community associated with a given resource is satisfied in QoWS (1 if the QoWS of the community c for the resource g is above the threshold, else 0) and UCA_{cg} is the water volume level of the really-depleted, defined by {high-3, medium-2, low-1}. The objective of defining the states in this way is to provide the identical priority among different communities, where the QoWS requirements are satisfied.

Again, the reward in Eq. (10) may be assigned in terms of the resource allocation mismatch:

$$R=-\Delta_{c,g}^{t}=-\mid\Phi_{c,g}^{t}-\Psi_{c,g}^{t}\mid. \tag{13}$$

The Q-learning aided resource allocation algorithm is detailed as:

Step1: Initialization, create a Q-matrix for each community with the initial elements of Q-values setting to 0.

Step2: Compute I_{cg},$QoWS_{cg}$ and UCA_{cg}, the value function and the reward R.

Step3: Compute the action probability φ, if $\varphi \leq 0.1$, then select random action; else select action corresponding to the maximum values of the Q-matrix for the current state.

Step4: Compute the reward and evaluate new state.

Step5: Update the Q-matrix. If convergs, ends the algorithm; else goes back to step2;

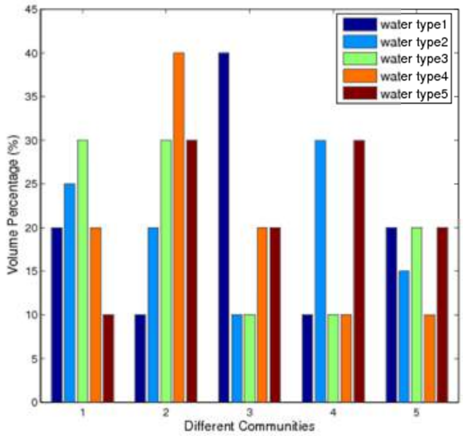

Figure 3: Volume percentage of different resources

5 SIMULATION RESULTS

In this section, we provide simulation results for evaluating the proposed water allocation schemes. Three types of contextual information are taken into account, including the information of the allocated volume, the QoWS, and the really-depleted volume. We assume there are 50 communities in SWG, and 5 types of water resources. In the Q-learning process, we set the learning rate $\alpha = 0.1$.

Fig. 3 depicts the water allocation percentage between different communities for a certain type of water resource. We select the scenario of 5 communities as an example to illustrate the diversity of the resource allocation, while guaranteeing the community users' QoWS requirements. Fig. 4 illustrates the water utilization efficiency. As expected, the proposed scheme achieves higher efficiency over the random allocation method. It implies that the proposed dynamics allocation approach has exploited the context information for adapting the dynamics of the SWG, thus leading to an improved efficiency.

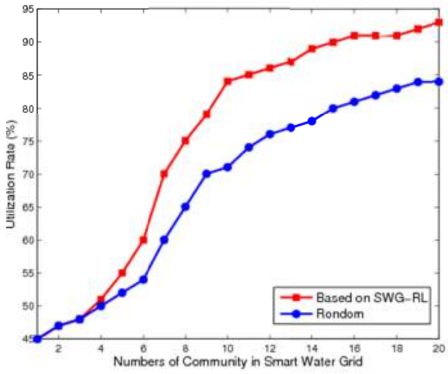

Figure 4: Water utilization efficiency

6 CONCLUSIONS

In this paper, we proposed a context-aware self-organized water resource allocation scheme for SWGs. A novel spectral clustering approach was developed for clustering end-users into water communities in terms of the end-users' profiles. A Q-learning aided dynamic algorithm was proposed to determine the optimal water allocation by virtue of the MDP approach.

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REFERENCES

[1] B. David, C. T. Yin, etc., "SMART-CITY: Problematics, techniques and case studies," *Proc. of 8th Int. Conf. on Computing Tech. and Infor. Management (ICCM)*, pp. 168 - 174, Aug. 2012.

[2] Y. He, Y. H. Liu, "Noninteractive localization of wireless camera sensors with mobile beacon," *IEEE Trans. Mobile Computing*, vol. 12, no. 2, pp. 333- 345, Feb. 2013.

[3] M. I. Mohamed and W. Y. Wu , "Power harvesting for smart Sensor networks in monitoring water distribution system," *Proc. of IEEE Conf. on Networking, Sensing and Control*, pp. 393 - 398, April 2011.

[4] J. Hayes and K. Tong, "A wireless sensor network for monitoring water treatment," *Proc. of IEEE Conf. on Sensor Technologies and Applications*, pp. 514 - 519, Aug. 2007.

[5] A. Ostfeld, "The battle of the water sensor networks: a design challenge for engineers and algorithms," *J. of Water Resources Planning and Management Division, ASCE*, Vol. 134, no. 6, pp. 556-568, 2008.

[6] M. Lin, Y. Wu and I. Wassell," Wireless Sensor Network: water distribution monitoring system," *Proc. IEEE Radio Wireless Symposium*, pp. 775 - 778, 2008.

[7] M. Mencarelli, M. Pizzichini and L. Gabrielli, "Self-Powered sensor networks for water grids: challenges and preliminary evaluations," *IEEE J. Sel. Areas in Telecomm.*, pp.1-8, Oct. 2012.

[8] F. L. Lewis and K. G. Vamvoudakis, "Reinforcement learning for partially observable dynamic processes: Adaptive dynamic programming using measured output data." *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 41, no. 1, pp. 14-25. 2011.

[9] S. Z. Niu, D. L. Wang, S. Feng, and G. Yu, "An improved spectral clustering algorithm for community discovery," *In Proc of IEEE Hybrid Intelligent Systems*, pp. 262-267, Aug. 2009.