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Risk based Multi-Agent Chilled Water Control System for a More Survivable Naval Ship

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Abstract - **We present a risk based multi-agent chilled water control system for naval ships which is able to reduce the vulnerability of the ship systems by automatically assessing threats and then reconfiguring the water distribution network prior to a damage event to minimize the impact. The multi-agent control system applies market-based approach to manage chilled water resource both reactively and proactively during runtime with risk assessment of component failure. In our study, an extended Contract Net Protocol (CNP) is proposed and used for the agent bidding and negotiation to respond to failures, failure risks and mission goal changes. The protocol extension covers both de-commit strategy and an innovative cost model which is able to include the risk factor in the agent bids and allows the control system act proactively. The effectiveness of the risk based multi-agent control has been demonstrated on a ship chilled water system simulator which mimics a reduced scale of chilled water system tabletop testbed to respond to threats, e.g., fire threats.**

Index Terms—**Multi-agent control, market-based approach, Rule Macro Controller and Mixed Integer Linear Programming**

1. INTRODUCTION AND RELATED WORK

Ship survivability is dependent upon the continued operation of ship combat loads [1], which are, in turn, dependent upon resources from ship auxiliary systems including ship electrical, chilled water, low pressure air, and hydraulic systems [2, 3, 4]. The high dimensionality of complex ship engineering systems often requires decentralized control concepts [4].

With current hard wired systems, ship survivability has greatly improved [3]. Current approaches to reduce the vulnerability of shipboard control system involve the use of redundant controllers; distributed *Programmable Logic Controllers* (PLCs) and wiring approaches that attempt to optimize fail-over capabilities [4]. Unfortunately, these approaches do not have the capability to anticipate the threat and take corrective action prior to a damage event. To solve this problem, we have used the multi-agent-based control system where risk factor to the resource agents has been added to proactively reconfigure the system before the damage events happen and make the system more survivable. To maximize the ship survivability, the single agents have to communicate and to interact in a suitable way to achieve a common goal.

Multi-agent systems have been proven to be very effective for intelligent and distributed control system design [5, 6, 7, 8, 9]. In the previous work [3, 10, 11, 12], multi-agent systems are proposed to be used in chilled water control, other fluid system control, and power system restoration control.

Work presented in [10] is a utility-oriented agent-based control network proposed to be a robust approach for the automated configuration of a chilled water plant. In this agent-based approach, complete information about the current system state needs to be shared amongst all the nodes in the network. Therefore, the system performance is penalized. Moreover, this approach does not consider re-configuration in the presence of faults. In [11], authors have presented a market-based multi-agent system for the re-configuration of the electric shipboard power system. They have utilized only the reactive approach. Their negotiation is only triggered when a faulty component can be identified through the on-board sensor system. In [3], authors discussed about the need of a multi-agent-based proactive fresh water control system but lacks in discussing any systematic approach, protocols, cost function, etc. Authors in [12] have presented the hierarchical architecture of multi-agent intelligent control for the autonomous operation of shipboard fluid system. The work is limited in proposing some academic guidance for raising the level of intelligence, reducing the manpower for ship operation, and increasing the mission effectiveness. Furthermore, in [13] a multi-agent system for fire simulation for ships is presented. Various implication and importance of fire simulation consideration is presented in this paper. In our work, as a potential ship survivability threat, we have considered *fire*.

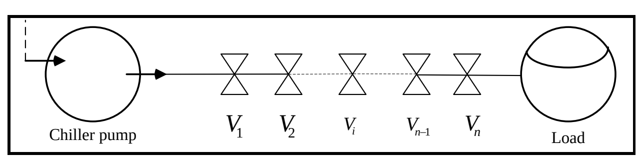

Fig. 1. Exemplary chilled water transportation route

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2. PROBLEM FORMULATION

Typically chilled water control systems for a naval ship involves 4 main types of components: load, chiller pump, valve, and pipe (see Fig. 1). The objective of the system is to cool the loads using chiller pumps through pipes and valves in an optimal way. Loads can obtain the chilled water from any of the chiller pumps through different pipes and valves. At the same time the chiller pumps can also serve different loads with priority. Chilled water control system provides information on unknown behaviors such as the directions of the chilled water flow inside the pipes that is obtained for specific valve configurations (chilled water routes).

This may be represented as typical resource allocation problem [14] where in order to utilize resources efficiently to meet application and system-wide requirements, the system must consider resource availability, control policies, and application's quality-of-service requirements. In other words, all components are situated in a distributed environment and each of them has different capabilities and beliefs. They are autonomous and can interact with one another, but make decisions individually. The loads need the chiller pumps to provide chilling water services and have to go through different pipes and valves, thus how to determine chiller pumps' availability, how to control valves' status in order to find a chilled water route with minimum total valves involved and shortest pipe length to reach the resource, and how to make the final decisions in an economical way, etc. are the major issues existed and needed to be solved.

Moreover, if on-board sensor systems indicate that there exists a disproportionate risk of damage to specific areas of the ship then the chilled water control system has to be reconfigured and therefore, involved resources have to be reallocated proactively. Similar resource re-allocation has to be also reflected in the reactive types (event are triggered if there exists a faulty component in the chilled water transportation route) of chilled water control system.

Our Novel Contributions:

We present a risk based multi-agent chilled water control system for naval ships, which is featured as follows:

a. Self-aware (through sensor and simulation based prediction), self-configurable (re-allocation of resources), self-organizing (risk factor in the cost function), and self-optimizing (agent-based negotiation to optimize cost) chilled water control system.
b. A hybrid cost metric including the risk factor of each component of the chilled water transportation route. The cost function is defined in a systematic way using the chilled water production cost, transportation cost, and the associated risk factor.
c. Extension of the contract net protocol for the multi-agent-based negotiation. The extension supports incorporation of the risk factor within the cost function and de-committing while risks exceed penalties, and allows the control system to be proactive.
d. A case-study analysis of our multi-agent-based chilled water control system using a scaled-down physical prototype of a real naval ship [2].

3. MULTI-AGENT-BASED CONTROLLER

We developed our chilled water control system using a multi-agent-based system. For inter-agent communication we have used contract net protocol. Multi-agent-based negotiation tries to optimize the system resources using our novel hybrid cost function.

3.1 Contract Net Protocol

The *Foundation for Intelligent Physical Agents* (FIPA) [15] defined protocol; CNP [16] is a widely used high-level protocol for distributed control system with *Belief–Desire–Intention* (BDI) multi-agents. In the multi-agent system, (agents with different capabilities and different beliefs) in order to find the right agent for the right task, CNP is a fast and flexible way with low communication costs. The utilization of CNP involves negotiation mechanism which is a fundamental mechanism and a time-consuming process. The optimal resource allocation is obtained through the negotiation among initiators (customer) and

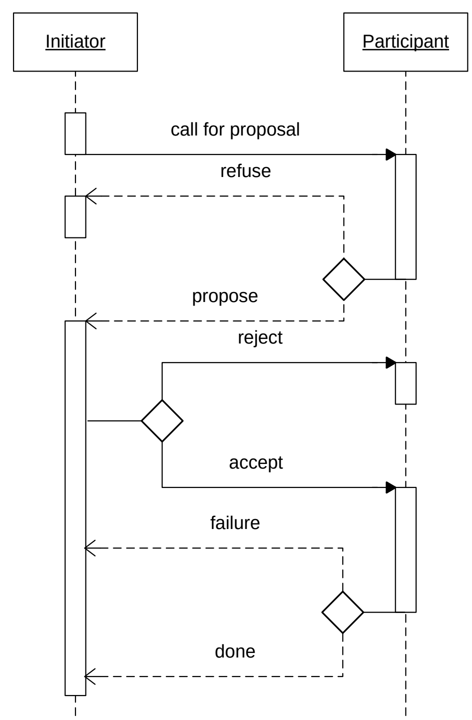

Fig. 2. The state-of-the-art FIPA CNP

participants (service providers) in two-sided markets[1]. In CNP, the relation between customers and service providers is initiated in a *Call For Proposal* (CFP) and an evaluation of the proposals submitted by the providers to the customers. For example, the proposal will be given a cost which corresponds to the actual execution of the tasks. The negotiation process shown in Fig. 2 begins by initiator agent (e.g. the load) who sends CFP to the participant agents (e.g. chiller pump) who are suited to perform certain tasks. The CFP includes a deadline by when proposals should be received by the initiator agent. The proposals received after the deadline will be automatically rejected with a given reason that the proposal has been late. The participant agents then make proposals or refuse the task accordingly and inform the initiator agent. Once the deadline passes, the initiator agent evaluates the received proposals, accepts the most appropriated proposal (e.g. lower cost to transport water) and rejects the rest, and assigns the task. Finally, the winner who is assigned the task reports back to the initiator agent to confirm whether the task is done or failed.

In order to solve the resource allocation problem described earlier in Section 2, the CNP is extensively used and further extended.

3.2 Cost Function for the Controller

In scope of this paper, we demonstrate a novel cost model for the multi-agent-based chilled water control system using heuristics and systematic cost function definition. The cost function is illustrated by using an exemplary chilled water route (see Fig. 1) that includes a load, valves (*n* valves: V_1 to V_n), and a chiller pump. Below we describe various parts of the overall cost function

3.2.1 Production cost model

The production cost, (typically associated with the chiller pump) is determined by the cost of the chiller pump being used for a given planning time interval t (e.g. an hour). Therefore, if the total water consumption is Q_p, the water price is W_p then the production cost C_p may be expressed as follows:

$$C_p = W_p \cdot Q_p \tag{1}$$

The inclusion of the water price in the production cost has facilitated us to incorporate varying water production cost of the chillers as the cost may vary due to the supply efficiency of the chillers and the utilized energy. Moreover, water pricing has facilitated the unification of the units for all the other parts of the cost model.

3.2.2 Transportation cost model

The transportation cost, which is related to the distance between the load and the chiller pump, may be represented using the water cost similar to the production cost model. For the planning time span t, the regular water flow rate F (gallons/h or tons/h) can be represented as follows:

$$F = \frac{Q_p}{t} \tag{2}$$

If the time for water transportation from chiller pump to the load is t_T (see Fig. 3), then the total chilled water consumption by the load can be calculated as:

$$W_T = F \cdot t_T = \frac{Q_p}{t} t_T \tag{3}$$

As the chilled water price of the chiller pump is W_p, the transportation cost C_T, may be expressed as:

$$C_T = W_p * W_T = \frac{W_p Q_p}{t} t_T \tag{4}$$

In Equation (4), for a specified chilled water flow rate, long distance means it takes more time for the chiller pump to transport chilled water to the load. Moreover, the cost model shows that the transportation cost is also corresponding to production cost.

3.3 Risk cost model

Risk factor has been included in our cost function to enable the control system proactive in case there is a component fault predicted in the chilled water transportation route (the controller reacts and reconfigure the resource allocation) or there is a potential disproportionate risk of damage to specific areas of the ship from threats.

In order to understand the risk cost model developed within the scope of this paper, we first derive the risk cost in a centralized way. As shown in Fig. 1, the cooling components for a specified load may be represented as a serial network, Therefore, if only one component, e.g. valve, in the chain (serial network) fails, the complete networks fails (chilled water will not be transported to the load from the chiller pump).

Let's assume, for the i^{th} component, the failure probability is U_i. Moreover, assume that all the components are independent and constant during the planning time t. Therefore, the unavailability of the cooling route k can be expressed as

$$U_k = 1 - \prod_{i \in k}(1 - U_i) \tag{5}$$

As discussed earlier in Equation (1), the chilled water needed for the planning period is Q_p, the expectation of chilled water loss will be:

$$Q_R = U_k Q_p \tag{6}$$

This means that if we take this route for cooling, it is supposed to supply chilled water of Q_p. Therefore, the expectation of chilled water supply is $(1 - U_k)Q_p$, where, chilled water loss is $U_k Q_p$ for the chiller pump. As we consider the chiller pumps as the seller in the multi-agent-based control system, the chilled water loss for chiller

[1] *Negotiation among multi-agent and the CNP to solve an optimization problem is compared with market-based negotiation, where bidding and winning varies. In our chilled water control system water cost can be compared with currency in an economic market.*

pumps means profits loss. Therefore, if the chilled water price is W_p, the loss for the seller will be:

$$C_R = W_p\, U_k Q_p \tag{7}$$

This part of cost shown in Equation (7) should be paid by the buyer, in this case the load. As a result, Equation (7) is utilized for risk cost evaluation. The risk cost of valves and chiller pumps may be defined in the similar way. Therefore, by combining the Equations (5), (6), and (7) we have:

$$C_R = W_p Q_p [1 - \prod_{i \in k}(1 - U_i)] \tag{8}$$

So far, the probability mentioned above is considered to be constant during the planning time *t*. However, we can also model it in a variable way.

Divide planning time span into *N* sections where each section lasts Δx hours as shown in Fig. 3. Therefore, total time planning time *t* can be represented as follows:

$$t = N \cdot \Delta x \tag{9}$$

In each section, assume the unavailability of the components is constant and the availability of j^{th} section is U_i^j. Therefore, the chilled water consumed by the load in this period can be approximated as:

$$Q_P^j = \frac{\Delta x}{t} Q_p \tag{10}$$

Therefore, the unavailability of route *k* is:

$$U_k^j = 1 - \prod_{i \in k}(1 - U_i^j) \tag{11}$$

and the expectation of chilled water loss is:

$$Q_R^j = U_k^j Q_p^j \tag{12}$$

Therefore, the risk cost in j^{th} section is $C_R^j = W_p Q_R^j$

Now we can calculate the risk cost in the whole planning time period as:

$$C_R = \sum_{j=1}^{N} C_R^j = \frac{W_p \Delta x}{t} \sum_{j=1}^{N} [1 - \prod_{i \in k}(1 - U_i^j)] \tag{13}$$

Both Equation (4) and Equation (13) calculate the risk cost in a centralized way. However, in the multi-agent system used for our chilled water control, the risk cost has to be evaluated in a distributed way. Therefore, to implement the risk cost in a distributed way, we obtain the risk cost of the cooling route in an iterative manner.

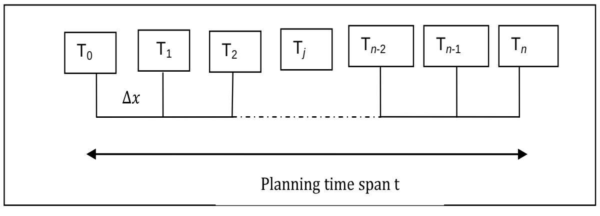

Fig. 3. The division of planning time span

Assume that the failure probability of the first component (see Fig 1) which should be a valve located in the neighborhood of the load is u_1. Therefore, the risk cost of the first component can be defined as:

$$C_R^1 = [1 - (1 - u_1)] \cdot W_p Q_p \tag{14}$$

For the second component located in the neighborhood of the first component, the risk should consider both these two components since they are located in serial. Assume that the failure probability of the component is u_2. Therefore, in the centralized way, the risk cost can be calculated as:

$$C_R^2 = [1 - (1 - u_1)(1 - u_2)] \cdot W_p Q_p \tag{15}$$

Equation (15) can be rewritten as:

$$C_R^2 = \{(1 - u_2)[1 - (1 - u_1)] + u_2\} \cdot W_p Q_p = (1 - u_2)R_1 + u_2 W_p Q_p \tag{16}$$

In this way, if we already know the risk cost of the upstream[2] neighborhood component, we can obtain the risk cost in a distributed way without information of other components. Therefore, we can implement the risk cost evaluation in a distributed way and we observe that the calculated risk cost is exactly the same as in the centralized approach.

Similar to Equation (15), if we already know the risk cost R_{i-1} from *1* to *(i-1)* components, then the risk cost from *1* to *i* should be:

$$C_R^i = [1 - (1 - u_1)(1 - u_2) \cdots (1 - u_{i-1})(1 - u_i)] \cdot WpQp \tag{17}$$

Similar to Equation (16), Equation (17) may be represented as:

$$C_R^i = (1 - u_i)[1 - (1 - u_1)(1 - u_2) \cdots (1 - u_{i-1})] \cdot WpQp + ui \cdot WpQp \tag{18}$$

Finally, Equation (18) can be expressed in distributed way as:

$$C_R^i = (1 - u_i)C_R^{i-1} + u_i W_p Q_p \quad (i = 2,3,4 \ldots n) \tag{19}$$

Therefore, Equation (19) may be used to calculate the risk cost of the complete chilled water transportation route from the load to the chiller pump in a distributed manner. In this model the risk cost of a component is dependent on both the failure probability of itself and also on the risk cost of upstream components.

3.4 The final cost function for negotiation

The final cost function required for the multi-agent based negotiation includes all the components: production cost, transportation cost, and the associated component-level risk factor. Typically, the production cost is directly associated with the chiller pumps and for the valves we

[2] *Water flows from the upstream agent to the downstream agent. The downstream/upstream relationship between two agents (e.g. valve agents) is determined during multi-agent-based negotiation.*

use the terminology operation cost (this helps us to built the cost for our prototype presented in Section 5). Operation cost is considered to be the cost associated with ing a physical component's state to meet the proposed chilled water route's requirements. If a task requires a valve open and if the valve is already **ON**, the operational cost for this valve will be 0, otherwise, there is a cost defined to toggle the valve's state. As discussed before, transportation cost is the total of the distances between each agent in the route. Therefore, our final cost is the sum of the operation cost and the transportation cost which is multiplied by a factor determined by risk due to the probability of failure.

4. CHILLED WATER ROUTE DISCOVERY

In our multi-agent-based chilled water control system, the route discovery process employs in a recursive way to select the best chilled water route from a load agent to a chiller pump agent. Similar to the CNP protocol described in Section 3.1, at the beginning, the initiator (load in our experiment) sends CFP to each participant agents who can be a chiller pump agent or a valve agent as a neighbor. The proposal includes the cost of the service that the neighbor agent can provide and an agent list that indicates the possible route (the list is empty initially for the load agent initiated CFP). If the initiator is a load agent, the agent will send CFP to all the chiller pump agents. It needs to be considered that in the following conditions, the initiator does not send the CFP:

a) The neighbor is already in the *"neighbors list"* as the agent who forwarded the CFP.
b) The neighbor is a load agent.

Finally, each neighbor recursively sends CFPs and returns the results to the initiator except if the neighbor is a chiller pump agent. The initiator then picks the best route returned by each neighbor and establishes a contract with the neighbor. A contract is an agreement between two agents that specifies the statuses of both agents. If the contract specifies that these agents are **ON**, then the contract represents an upstream/downstream relationship between the two agents. An agent can initiate an upstream/downstream relationship by accepting a proposal elicited from a neighboring agent with a CFP. The only non-adjacent agents that enter into contracts with each other are load agents and chiller pump agents. The relationship represents the load agent's final chilled water route selection. Also, under the following conditions the neighbor can refuse a CFP:

a) The neighbor is in a **BROKEN** state.
b) The neighbor has already a contract with other initiator and the proposed route conflicts with the currently selected contract, e.g. the chilled water flow direction.

The cost of the proposed route is calculated using the systematic approach presented in Section 3.

Once a route has been selected by the load agent, the participant agents in that route must be informed. In our route discovery process, it is assumed that each load agent and chiller pump agent has only one connected neighbor, e.g., one valve agent.

To enable the load agent to manage recursively several negotiation processes, we have introduced two phases of proposal acceptance by extending the typical phase *Accept* of the original state-of-the-art CNP with two new phases: *PreAccept* and *DefinitiveAccept*. Therefore, we obtain a new negotiation process described in Fig. 4.

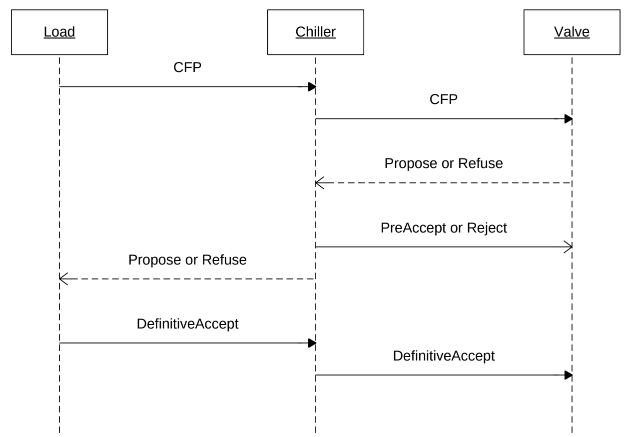

Fig. 4. Extension of the CNP for the negotiation

In Fig. 4, a load agent l sends CFPs to all chiller pump agents $(c_1 \ldots c_t)$. The agent c then asks the neighboring valve agents $(v_1 \ldots v_n)$ and then the valve agents recursively send the CFP to other neighboring agents. The negotiation process will not be stopped until v_n reaches agent l and responds back. If the negotiation process is between the agent c (chiller pump agent) and the agent v (valve agent), the initiator sends the best participant a *PreAccept*, but rejects all the other participant agents. In this way, the participants do not to wait unnecessary time for a response from the initiator and the whole negotiation process will not be blocked. Since all agents are cooperative, eventually, the best chilled water route can be selected by the agent l. The agent l then sends the *DefinitiveAccept* to the selected agent c_s, and the *DefinitiveAccept* will be recursively sent to all participant agents which has been *PreAccepted*.

Finally, at the last phase of CNP, the participant agent has to report back the final state of the task to the initiator. In our experiment, the task is to ask the participant agent to switch its state to **ON**. However, according to the constraints, if the participant agent is in **BROKEN** state or the contract is with chilled water flow direction conflict, the state changing operation of the component (valve) may not be performed. Moreover, state changes of the participants may also occur after it has been *PreAccepted*. Therefore, a *de-commitment* phase is considered in the participant side in our proposed CNP as shown in Fig. 5. The participant agents can choose to perform the task or *de-commit*.

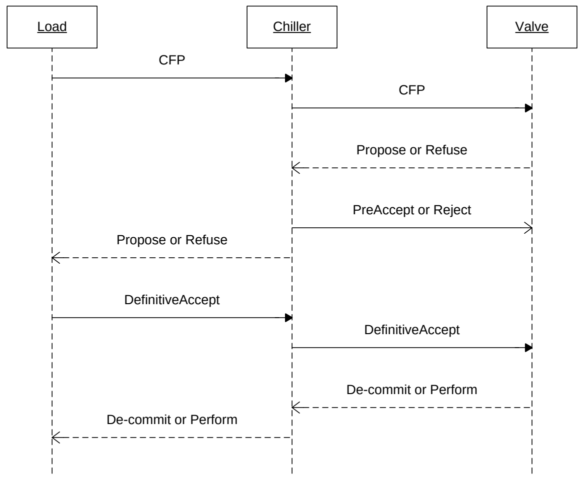

Fig. 5. Proposed CNP for proactive control system

4.1.1 De-commitment Strategy for Negotiation

In our proposed CNP, the de-commitment phase is triggered when the status of the agents (valve agent or chiller pump agents) are changed. The status changes can be for example: the agent status of the contractor state is changed to BROKEN or the total cost of the chilled water transportation from the chiller pump to the load surpasses a threshold that is no longer the most economical route. In such a scenario, previously committed contract can be broken and a new contract is re-negotiated. Moreover, in some scenarios, when combinations of all the chillers may not be able to supply needed cooling, the system will have to shed all non-vital loads to provide maximum cooling capacity to the vital loads.

Typically, identifying a broken (faulty) component within a chilled water transportation route is simple but to determine the threshold that allows the contractor to decommit is a complex problem. In our control system, for a contractor who has been in a contract, the only cost that can be changed is the risk cost. Assume that the set time of a contract is *T* to indicate a time stamp when the contract is established. Therefore, for the *T*, the cost can be written as the follows:

$$\mathbf{C_T = C_R^T} \tag{20}$$

When the state of the contractor is changed due to the change of the associated risk cost, the new cost for the current time will be:

$$\mathbf{C_C = C_R^C} \tag{21}$$

Accordingly, the new risk $\boldsymbol{r}$ can be used to determine the threshold as a penalty coefficient:

$$\boldsymbol{\alpha} = \mathbf{1 - r} \tag{22}$$

If the new cost is greater than the sum of penalty cost and $\boldsymbol{C_T}$, then the de-commitment can be made by the contractor, otherwise the contractor cannot break the contract.

Therefore, if

$$\mathbf{C_C > C_T + \alpha C_T} \tag{23}$$

the contract will be broken.

5. RESULTS AND CASE STUDY ANALYSIS

Fig. 6. Tabletop prototype

The Tabletop shown in Fig. 6 (schematic shown in Fig. 7) is a scaled-down physical prototype of a real naval ship chilled water and electrical system [18]. The system includes plumbing, controls and communications, and electrical components that mimic real-life operations. Specifically, the Tabletop schematic test bed shown in Fig. 7 represents the chilled water transportation system for the load cooling. This prototype is capable in providing information on unknown behaviors such as the directions of the chilled water flow inside the pipes that is obtained for specific valve configurations (chilled water routes). The Tabletop includes 4 main subsystems: loads, chiller pumps, valves, and pipes. There are total 6 loads, *L01* to *L06*, where *L05* and *L06* are vital loads. This test bed does not simulate the actual heat transfer of each load. Therefore, 6 flow meters are installed next to the loads to indicate if there is chilled water service or not. High loading conditions will require that non-vital or low priority loads to be shed from the cooling loop. The chilled water services in-

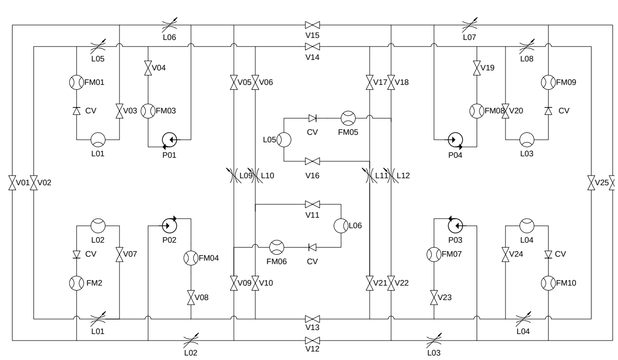

Fig.7. Tabletop schematic

clude 26 valves to transport chilled water from chiller pumps to loads for cooling purpose. Moreover, the Tabletop also simulates the electrical systems with 8 redundant power panels. The controls of the relays for electrical system are not included in the scope of this work.

Prototype Validation A testing scenario has been developed using a simulation environment presented in Fig. 8. The Tabletop and other associated models used for the simulation are shown in Fig. 8. Later for the proactive control performance testing, the paper considers fire threats.

publish messages by sending them to the SB server. The server then redistributes the message to all clients who previously subscribed to the corresponding channel.

Stimulator: The Stimulator presents scenarios to multi-agent-based controller by producing faults and mission objectives[3] messages and records all activity in the system for post-scenario analysis. The Stimulator interacts with the Tabletop simulator for injecting component faults which are later reflected in the respective component states sent by the Tabletop Simulator to the controller. The Stimulator is capable to running tests by stimulating predefined faults (single as well as a combination) in batch mode.

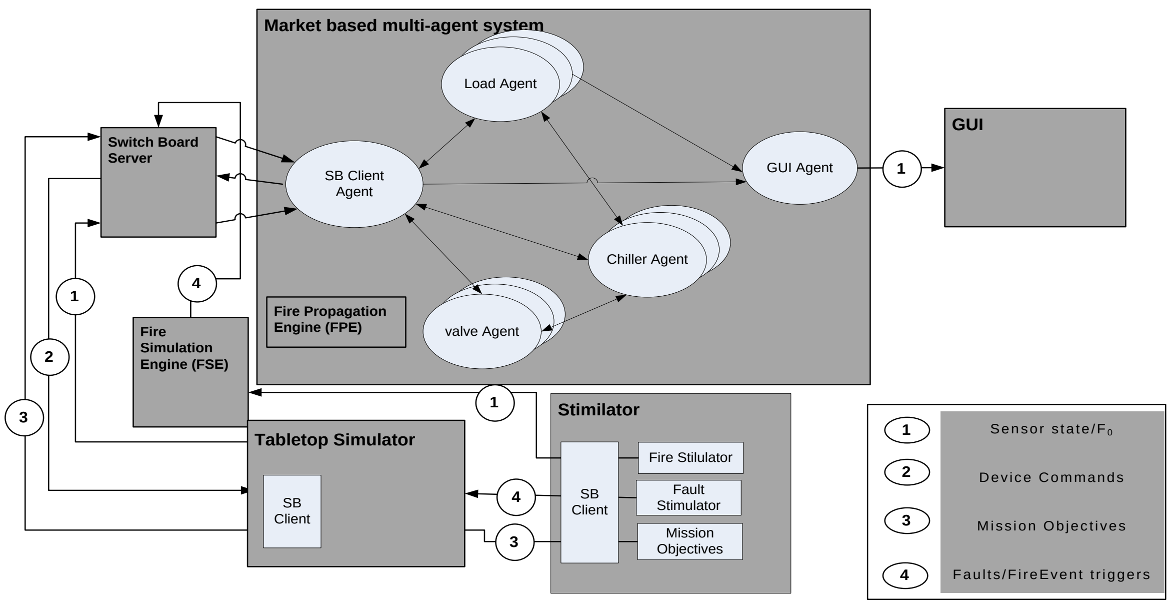

Fig. 8 Multi-Agent based Tabletop control schematic

Tabletop Simulator: A Tabletop Simulator is a software simulation of the hardware Tabletop (see Fig. 8) to enable our multi-agent-based control algorithm analysis. This simulator is written in Matlab/Simulink. It can simulate and send sensor state, as well as observations of the various electrical and fluid components and can act upon commands originating from the controller. Moreover, it can receive fault signals during the stimulation. The communication between the Tabletop simulator and other components is facilitated using the Switchboard infrastructure.

Fire Simulator: A Fire Simulation Engine (FSE) has been augmented to Tabletop Simulator to simulate a fire event, propagation scenario in compartments of a ship and resulting component failures. It has been developed to predict the fire spread and total heat release rate of the fire in the compartments.

Switchboard Infrastructure (SB): The switchboard application provides the communication infrastructure for all software components within this integrated simulation. It implements a *publish/subscribe* communications model that promotes loose coupling of software components. The SB server in Fig. 8 is a standalone application to which the SB clients running inside the software components subscribe for messages on a per-channel basis. Clients also

Multi-agent-based controller: The multi-agent-based controller generates control commands to the Tabletop simulator in order to satisfy the mission objectives sent from the Stimulator. Every controllable component in the Tabletop simulation has a corresponding agent in the multi-agent system. The SB client forwards the mission objectives message from the Stimulator to the load agents. Based on their objectives, each load agent starts the chilled water service negotiation process with the available chiller pump agents using our proposed CNP. The chiller pump agent in turn initiates the route discovery process to the load by calling for proposals from the neighboring valve agents. This CNP process is cascaded to the valve agents where each value initiates the negotiation with the neighboring valve until the route discovery is converged at the requested load. The agent in the controller has a state which is derived from the *ground truth* of the corresponding component in the Tabletop Simulator. This information is received by the SB client agent in the form of *sensor state*

[3] Typical mission objectives for a naval ship includes: Cruise, Battle, Secured and Port mode. Mission-based control is an important research area [17].

messages which is forwarded to the corresponding agent. For the anti-threat behavior upon fire event, in order to associate probable impacts of inbound threats with components of the ship auxiliary control system based on the *Fire Propagation Engine* (FPE), we set up a test of the predictive capability of the FPE to assure the model yields acceptable results, regardless of its simplicity or complexity and to obtain a better understanding of it. Details of FPE are out of the scope of this paper.

In the following, we have compared our multi-agent-based controller with the state-of-the-art controllers [18] for chilled water transportation. Authors in [18] have presented two controllers: (1) *Rule-Macro Controller* and (2) Mixed-Integer Linear Programming (MILP) solver based controller (*Searched-based controller*). Moreover, during comparison, we have collaborated with the group considered similar matrices as the authors in [18] have used.

Performance Evaluation Matrices

In order to evaluate the performance of multi-agent-based controller over time we use performance using the *Capability* and *Utility* metrics similar to [18]. The following definitions of *Capability* and *Utility* have been considered.

The metric *Capability* is used to track the percentage of loads that are operational at any given time. A load may be considered operational if it is powered ON and if it's thermal and power requirements are met. Equation 24 defines *Capability C* as follows:

$$C(t) = \frac{1}{N}\sum_{i=1}^{N} L_i(t) \qquad (24)$$

Where, *N* is the total number of operational loads (6 for our Tabletop simulator shown in Fig. 6 and Fig. 7) and *Li* means whether load *i* is operational or not.

The metric *Utility* combines load operability with system costs in order to determine the cost it incurs for keeping the loads operational. Typically, these costs are composed of transient penalties for switching component states, continuous penalties for keeping components in use, and a penalty for losing chilled water due to faulty pipes. Equation (25) defines *Utility U as follows*:

$$U(t) = C(t) + c_S S(t) + c_T T(t) + c_K K(t) \qquad (25)$$

Where, *C* is the *Capability* defined in Equation (24) and *S*, *T*, and *K* are the switching, continuous, and leak costs, respectively. *cS*, *cT*, and *cK* are the negative constant coefficients used to relatively weight each cost category. For the evaluation presented in Fig.9 and Fig. 10 these coefficients are taken as follows: *cS* (-0.01), *cT* (-0.001), and *cK* (-0.5), respectively (similar to work presented in [18]). In Equation (25), switching penalty *S* is the total number of state switches for loads, pumps, relays and valves that have occurred since *t=0*. *S(0) = 0*. Moreover, continuous penalty *T* is the number of seconds that loads and pumps are in use where, *T(0) = 0*. Finally, leak penalty *K* may be defined as:

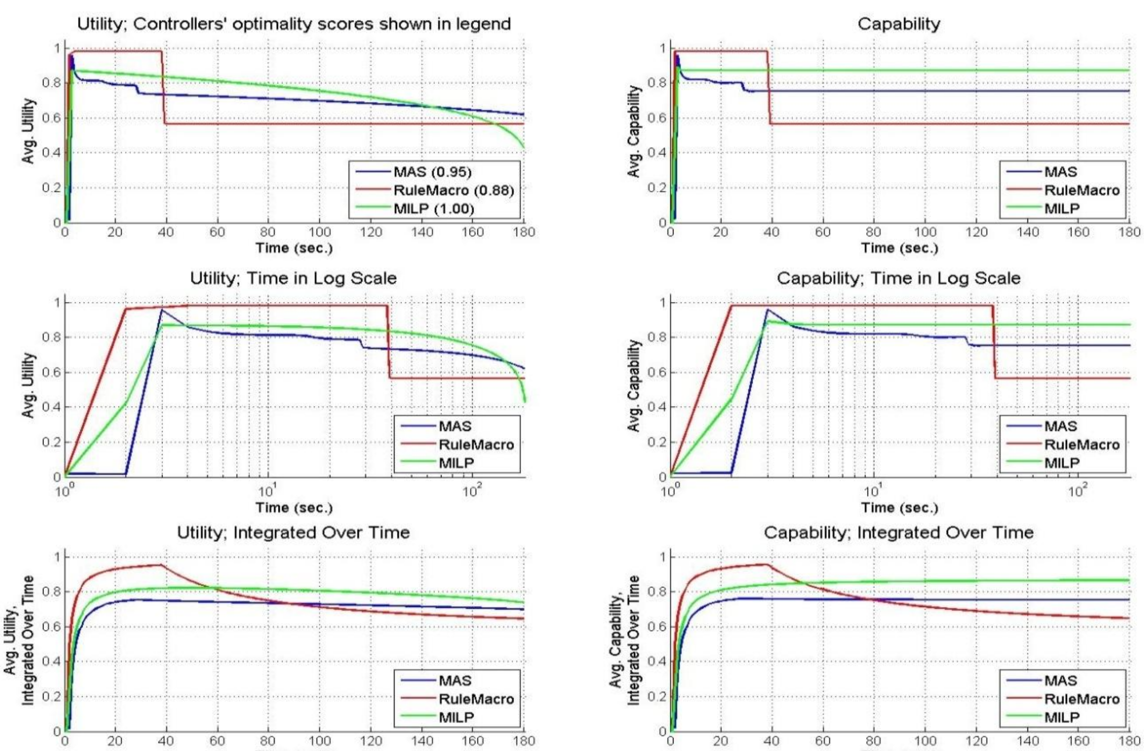

Fig. 9. Comparison our multi-agent-based controller compared to searched-based and rule-macro controllers

$$K(t) = \frac{W(0)}{W(t)} - 1 \qquad (26)$$

In Equation (26), *W(t)* is the amount of chilled water in the water subsystem at time *t* and *W(0) = 0*.

We compare our controller with the controllers presented in [18] using the above mentioned metrics. For an accurate comparison, we need to understand fundamental principles of the two algorithms presented in [18]. Below a short summary is provided. For details see [18].

Rule-Macro Controller

In a *rule-macro controller*, system state is received by the controller and stored within a collection buffer. Predefined fault conditions determined at design time e.g., a particular valve is *stuck-closed* are stored as *rules*. The response of such a *rule*, e.g., open a different valve to redirect chilled water is stored as a *macro* and is executed when the fault condition of the rule is satisfied. For our evaluation, the *rule-macro controller* used for the chilled water control system contains 104 *rules* and 96 *macros* in order to satisfy the mission objective of the combat ship (similar to [18]).

The major benefits of this controller are: (i) reactive reconfiguration is limited to a predefined set of *rules-macros*, and (ii) reconfiguration occurs very fast due to the simple computational complexity of evaluating *rules* and executing *macros*. The major drawback for such a controller is that no realizable set of *rules* will be enough to address the entire combination of the *rule-macro*. For our experiment, the *rule-macro controller* is limited to only respond to a predefined set of most common faults.

Mixed-Integer Linear Programming Solver Based Controller (Searched-based Controller)

This controller models the chilled water transportation system as a connected graph and formulates a Mixed-Integer Linear Programming (MILP) problem based on system constraints and mission objectives. After that it searches for the optimal system reconfiguration. Therefore, it is sometimes called a *searched-based controller*. This controller uses dynamic system state to accurately update system constraint set and incorporates the changing mission objectives into the objective function. Therefore, intuitively the controller solves the optimal set of variables that is converted into system reconfiguration commands.

The strength of this controller is its capability to use an efficient linear programming solver to find the best reconfiguration in response to component faults. The major drawback is that this approach becomes intractable when the system complexity gets increased.

The comparison of the reactive capability of our multi-agent-based controller (MAS) over *rule-macro controller* and *searched-based controller (MILP)* can be seen in Fig. 9. This experiment has included 400 trials for each controller. Each trial had the same *mission objective* – all loads were preferred ON. Each trial had a different fault scenario with a random combination of around 1 failed pump, 2 valves stuck closed, 1 leaky pipe, <1 failed power supply, and 2 relays stuck open.

The results plots show the *Utility* & *Capability* [18] achieved by each controller averaged over 400 trials. Each instance of a leaky pipe in this test set refers to a pipe through which half of the water is lost. Controllers have a choice as to whether they should provide a load with chilled water even if it means transporting this water through a half-leaking pipe.

As one can see by looking at the steady-state values of the *Capability* plot in Fig. 9, multi-agent-based (MAS) controller satisfies fewer objectives than searched-based (MILP) does, but because MAS leaks less water than MILP it achieves higher *Utility* than MILP after *t=140* seconds. MAS outperforms *rule-macro* in terms of *Capability*, and despite leaking water it achieves higher *Utility* on an average for the first three minutes after a fault occurs. Therefore, multi-agent-based controller achieves the best balance between achieving load operability and preventing lost resources.

State-of-the-art controllers [18] are not implemented to be proactive by incorporating various fault-prediction engines, e.g. fire propagation engine. To demonstrate the proactive capability of our agent-based controller, we tested our controller using a set of 20 fire scenarios. Each scenario contained one random compartment to simulate a fire model at t=10 seconds.

Fig. 10 shows the average *Capability* and *Utility* achieved by the multi-agent-based controller across all fire scenarios at any given time.

It can be observed from Fig. 10 that our controller is capable to be reconfigured proactively to a fire event. In this simulation, when we have introduced the fire event for a random compartment at *t=10* seconds. We may observe that the Agents' status has been changed to **BROKEN** on

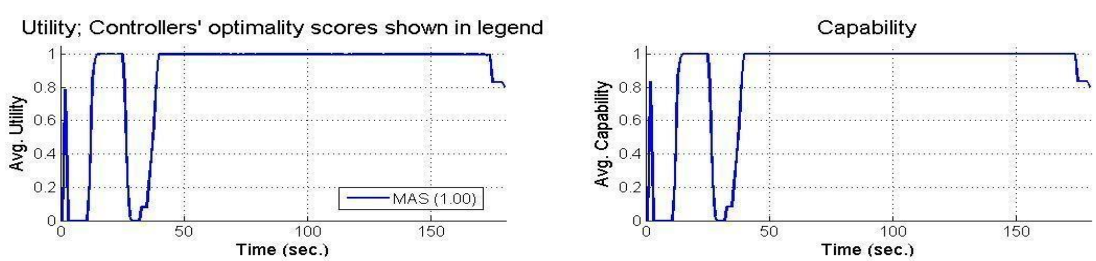

Fig. 10. Proactive capability testing or multi-agent-based controller using fire propagation model

an average at $t=40$ seconds. When the pump agents turned to broken, the system will reconfigure/reroute and command the working valves to supply chilled water to the loads. We can observe in Fig. 10 that the *Capacity* and *Utility* remain the same from $t=40$ seconds to $t=160$ seconds, which clearly demonstrates the proactive behavior for the multi-agent controller. During the last 20 seconds, the curves came down. This is because in some of the scenarios, all of the agents including load, valve, pipe, and pump agents are broken at that time. Therefore, *Utility* and *Capacity* will correspondingly go down on an average.

6. CONCLUSION

A risk based chilled water control system for the naval ship based on multi-agents has been presented in this paper. Our control system reduces the vulnerability of the ship systems by automatically assessing ship threats and then reconfiguring the ship chilled water system prior to any damage event to minimize the impact. We developed a systematic approach of cost function definition where risk factor may be included. Utilizing this new definition of cost function, we have extended the state-of-the-art CNP to adapt the multi-agent-based control system to be proactive. Finally, we have demonstrated our controller in a use-case using the Tabletop prototype. We have compared our multi-agent-based controller compared to the state-of-the-art chilled water transportation system controllers. Moreover, we have demonstrated the proactive-capability of the multi-agent control system in the presence of fire events.

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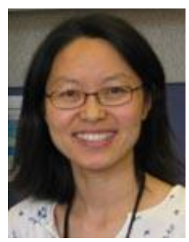

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