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Application of Intelligent Control to Material Circulation in Advanced Life Support Systems

Hiroyuki Miyajima
Tokyo Jogakkan College

Tomofumi Hirosaki
Space Systems Development Corporation

Yoshio Ishikawa
Nihon University

ABSTRACT

This paper discusses the integration of intelligence into the supervision and control system of an Advanced Life Support System (ALSS). An ALSS is a complex, large-scale system that should be maintained solely by a small crew. Since an ALSS is operated far from Earth, the propagation delay of radio waves makes remote support from Earth difficult to implement immediately. Accordingly, an autonomous supervision and control system is essential. A supervision and control system comprises an automatic controller for ALSS equipment and crew who supervise the equipment conditions and operate it. The application of intelligent control to such an automatic controller reduces the load on the crew, allowing them to concentrate on their major missions. The concept of intelligent control proposed here is based on the SRK model that expresses human behavior with three cognitive behaviors. This paper utilizes simulation to verify the effectiveness of the proposed methods for intelligent control.

INTRODUCTION

The Advanced Life Support System (ALSS) is a life support system (LSS) for accommodating prolonged missions far from Earth. It is distinguished from an LSS for International Space Stations (ISS) by food production, biological processing in addition to physicochemical processing, and resource recovery by recycling human excreta or inedible crop portions [1]. Typical missions assumed include manned Mars exploration, which is 150 days for the outward trip, 619 days for the Mars stay, and 110 days for the return trip for an 879 days mission [2]. An ALSS, a complex and large-scale system, is hard for a small crew to maintain on their own. In order for the crew to concentrate on their major missions, it is essential that intelligence be integrated into the ALSS supervision and control system. Moreover, the propagation delay of radio waves makes remote support from Earth difficult to implement immediately in an ALSS operated far from Earth. This also encourages an autonomous supervision and control system.

A general supervision and control system is schematically defined in Fig. 1, which comprises an automatic controller for the ALSS equipment and crew who supervise the equipment conditions and operate it. This study aims to reduce the load on the crew by integrating intelligence into the automatic controller. Integrating intelligence includes realizing operation based on a long range perspective comprehending overall conditions and even future goals (strategic control), as well as determining the equipment operation based on the present conditions (opportunistic control), and determining the equipment operation based on predetermined rules (tactic control). Such control can be standardized based on the SRK model that expresses human behavior with three cognitive behaviors. This study discusses applying intelligent control based on the SRK model to the supervision and control system of an ALSS.

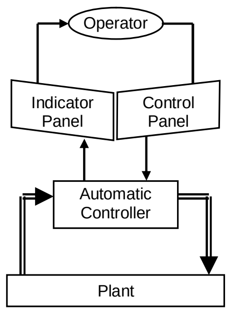


Fig. 1 Supervision and control system [3]

CONCEPT OF INTELLIGENT CONTROL

First is describing the concept of intelligent control addressed in this paper. Generally, intelligence is defined as follows: (1) potential to learn from experience, and potential to memorize knowledge acquired therein, (2) potential to adapt to new conditions and address them, and (3) potential to think conceptually and solve problems by inference. These types of potential are not special, and people use them in ordinary actions. Given this point of view, the SRK model, with which Rasmussen expresses human behavior, is helpful to study intelligent control. Rasmussen argues that human behavior can be expressed by the three levels of cognitive behavior shown in Fig. 2, which are skill-based, rule-based, and knowledge-based.

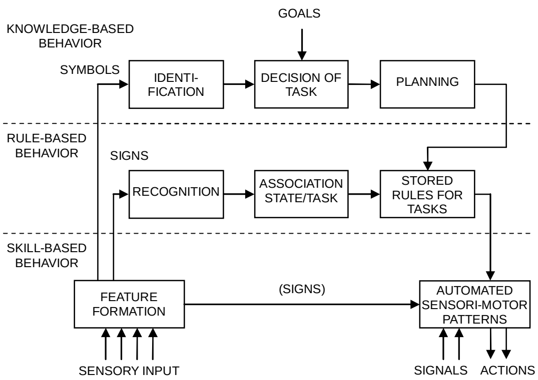


Fig.2 SRK model [4]

Skill-based behavior is action following the automated activity pattern from sensations, that is, automatic and smooth actions in very skillful routine tasks by humans. Sensory information is regarded as a quantitative "signal" that represents the behavior of a system. Then, action according to the error signal from the intended state is output.

Rule-based behavior is action to intentionally apply rules and procedures acquired through past experience and education. Such empirical rules are structured to be activated based on past successful experience, and are chosen by comparison with the pattern of sensory information. Sensory information in rule-based behavior is perceived as a "sign." A sign is a pattern of information that represents the state of a system coordinated with a certain action based on experience.

Knowledge-based behavior is action determined in a goal-driven manner at a conceptual level of a higher order, when no procedures or rules acquired from experience are applicable in unknown or unfamiliar conditions. This action uses knowledge expressed by a mental model to recognize the state of a system from its functional properties. Next, action required for goal achievement is designed and performed by a means-ends analysis of the recognized state and mental goal. The procedure overrides the rule of rule-based behavior for tasks which has not been learned yet. A plan may be corrected based on feedback from the execution results. Sensory information in knowledge-based behavior is perceived as a "symbol", selective abstraction representing the functional properties of a system, and is employed for inference and calculation for recognizing or estimating the state of a system.

PROCEDURE OF INTELLIGENT CONTROL

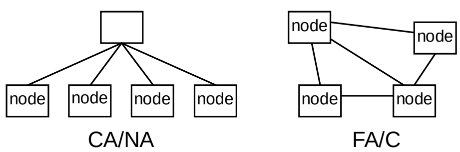
The intelligent control proposed in this paper consists of three classes based on the SRK model: Skill-based, rule-based, and knowledge-based levels. The 3T intelligent control [5] exemplifies the application of hierarchical control consisting of three classes similarly to the water regenerating system of an ALSS. Here we propose the following intelligent control.

SKILL-BASED CONTROL

The basic unit for the application of skill-based control is each individual sensor and actuator. Skill-based control employs feedback control used in conventional control theory.

RULE-BASED CONTROL

The basic unit for the application of rule-based control is a function that is part of a system. A function is "an action" taken to achieve a goal. Rule-based control is distributed control that makes decisions for every function. The type of distributed control is not CA/NA (completely accurate and nearly autonomous) but FA/C (functionally accurate and cooperative) as shown in Fig. 3. Each learning subject (agent) cooperates and decides independently in rule-based control. Each agent autonomously acquires control rules on-line in cooperation using Reinforcement Learning. That is, rule-based control is a multi-agent system. These state-action pairs correspond to Signs in the SRK model. The control rules are organized by the sign. Moreover, each agent is a symbol in knowledge-based control.



CA/NA: The given problem is divided into sets of sub-problems completing within each processing node (goal-driven problem solving).
FA/C: Each processing node attempts to solve the given problem based on incomplete input data in parallel, cooperating to derive a compatible solution as a whole (data-driven problem solving).

Fig. 3 Types of distributed control

Q-Learning is used as a Reinforcement Learning method. Q-Learning computes an action-value function to a state-action pair referred to as a policy. The value of this function is referred to as a Q-value. A Q-value for each action in a state is learned, enabling it to acquire the optimal action that should be taken in that state. The Q-value a_t the time of taking Action a in State x is expressed as $Q(x, a)$. A set of Q-values corresponding to all States x and Actions a is referred to as a Q-table. The agent's choice of Action a_t in State x_t at Time t results in State x_{t+1} and Reward r_t. Thus the Q-value is updated as follows:

$$Q(x_t, a_t) = (1-\alpha) Q(x_t, a_t) + \alpha \left(r_t + \gamma \max_{a_k} Q(x_{t+1}, a_k) \right) \tag{1}$$

where α is a parameter called the learning rate and $0 < \alpha <= 1$. A smaller learning rate implies that the previous estimate is considered important, while a larger learning rate means the present result is considered important. γ is a parameter called the discount rate, and $0 <= \gamma <= 1$. This is the ratio that represents the weight of importance at present of the reward to be acquired in the future. An action with the highest Q-value of all actions that can be chosen in a state is the best and that with the lowest value is the worst.

Designing state space

Hirosaki introduces a risk level in order to design state space [6]. The risk level is an index that divides the quantity of substances in a module or tank into several levels to express the quantity discreetly. In this study, the risk level of states is represented by seven stages as shown in Table 1. A positive value means that the substance quantity is too great compared to the target, while a negative value means that it is too small. The bigger the absolute value of the risk level is, the more dangerous the state is. A state is defined using the combination of risk levels of modules or tanks with which the agent equipment is connected.

Designing reward

Reward is defined as the degree of improvement in the risk level *risk*. When the quantities of the substances in the modules or tanks connected are measured as N, Reward r_t at Time t is expressed by Eq. (2).

$$r_t = \sum_{k=1}^{N} \left(\left| risk_{k(t)} \right| - \left| risk_{k(t+1)} \right| \right) \tag{2}$$

Action selection method

Using a random policy in a Reinforcement Learning problem produces a problem of huge time steps being required for convergence. Therefore, it is common to use a Q-value both during and after learning. According to a Q-value in the Q-table, an action is chosen stochastically by the ratio of value of each rule. The Boltzmann distribution of the following equation is used to compute this ratio,

$$\pi(x, a) = \frac{e^{Q(x,a)/T}}{\sum_{a_i \in A} e^{Q(x,a_i)/T}} \tag{3}$$

where $\pi(x, a)$ represents the probability that Action a will be chosen in State x, and T is the Boltzmann temperature. A random action is chosen as T is large, while a greedy action is chosen as T approaches 0.

KNOWLEDGE-BASED CONTROL

The basic unit for the application of knowledge-based control is a mental model expressed with symbols, which are causality between agents in rule-based control. That is, knowledge-based control is a single agent system based on a mental model. Figure 4 illustrates the functional structure of an ALSS, showing only those functions related to circulating O_2 and CO_2. Figure 5 expresses a mental model representing the causal relationship of the attributes of such sub-function. An action plan essential for goal achievement is designed using fuzzy inference on a conceptual level. Knowledge-based control overrides the rule of rule-based behavior for tasks which has not been learned yet.

Here we have exemplified knowledge-based control by designing an operation schedule for a solid waste processor when the crop cultivation schedule is modified. Based on the mental model in Fig. 5, a schedule is designed in a goal-driven fashion using the functional structure of the ALSS in Fig. 4. If the production of organic matter drops in Fig. 4, then food production falls (s1). If food production falls, then waste regeneration decreases (s2). The O_2 supply, CO_2 regeneration, and waste generation all decrease (s3). Furthermore, if waste decreases, then solid waste quantity decreases, and O_2 usage and CO_2 generation decrease (s4). These phenomena are accompanied by a time lag such as a cultivation period. The operation schedule of the solid waste processor must be designed for addressing such conditions, maintaining balance with the human metabolism. The operation of the solid waste processor is determined using the fuzzy control rule in Eq. (4). The fuzzy control rule expressed in Eq. (4) is described in Table 2. These rules are given by control system designer. Fuzzy variables for *risk*, the risk level for the O_2 and CO_2 tanks, and p, the sequence start probability of the solid waste processor, are set as shown in Figs. 6 and 7. These settings are made by providing qualitative rules inferred from Fig. 5. The sequence of the solid waste processor for a batch consists of raw material inflow, heating, pressurization by oxygen inflow, re-heating and re-pressurization, execution of first reaction, execution of second reaction, temperature and pressure reduction, purge of decomposition fluid, and purge of waste gas, operation time is 8 hours. The center-of-gravity method is employed for unfuzzying p (to return to a real value from a fuzzy quantity). The procedure makes schedule which is described as sequence start probability at time t.

$\boldsymbol{R_i}$: If x_1 is A_{i1} and x_2 is A_{i2} and x_3 > W3_W then p is B_i ,

$i = 1,2,\cdots,13$
(4)

x_1: O_2 quantity in the O_2 tank,

x_2: CO_2 quantity in the CO_2 tank,

x_3: Waste in the waste tank,

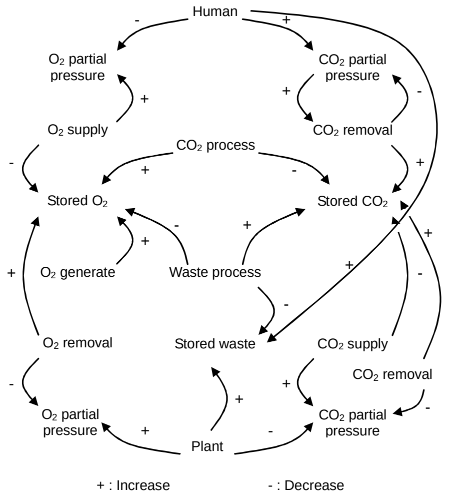
p: Sequence start probability of the solid waste processor,

W3_W: Waste per batch,

A_{i1}: A fuzzy set defined by $\boldsymbol{X}_1$ (set of the values of x_1),

A_{i2}: A fuzzy set defined by $\boldsymbol{X}_2$ (set of the values of x_2),

B_i: A fuzzy set defined by $\boldsymbol{P}$ (set of the values of p).



Showing only attributes of the sub-function related to circulating O_2 and CO_2

Fig. 5 Mental model for causal relationship of ALSS

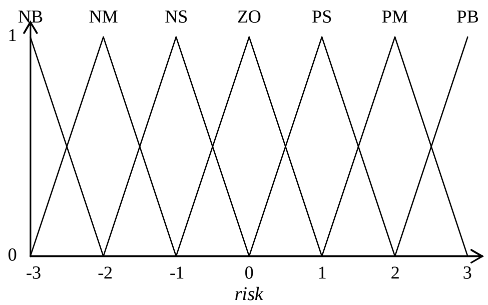


Fig. 6 Fuzzy variables for the risk level

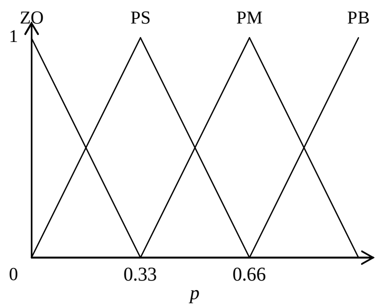
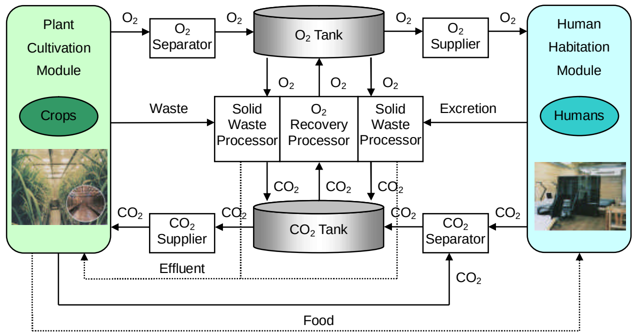


Fig. 7 Fuzzy variables for the sequence start probability of the solid waste processor

DESCRIPTION OF THE ALSS MODEL

Fig. 8 shows the material circulation system of an ALSS discussed as an example. As our objective is to confirm the effectiveness of an intelligent control, only substances related to circulating O_2 and CO_2 are modeled.



Only substances related to circulating O_2 and CO_2 are modeled.

Fig. 8 ALSS Material Circulation System

PLANTS

Plant growth is modeled by a logistic function [7]. Plant photosynthesis, that is, biomass increase rate per unit area dx/dt is given by;

$$dx/dt = \alpha x\left(1 - x/x_m\right) \tag{5}$$

where x: biomass [g/m^2], x_m: the maximum biomass [g/m^2], and α: photosynthesis coefficient [1/day]. x_m is defined by the plant type, and α is determined by environmental factors such as light intensity, temperature, and carbon dioxide concentration;

$$\alpha = f\left(I, T, co2\right) \tag{6}$$

$$\alpha = \alpha_{avg} \cdot \alpha_I \cdot \alpha_T \cdot \alpha_{co2} \tag{7}$$

where I: light intensity [μmol/m^2/s], T: temperature [deg-C], and $co2$: carbon dioxide concentration [ppm]. α_{avg} is the average photosynthetic rate. α_I, α_T, and α_{co2} represent the effects of light, temperature, and carbon dioxide concentration on plant growth with a dimensionless function. α_I and α_{co2} are as shown in Eqs. (8) and (9). α_T is assumed to be constant at 1.

$$\alpha_I = a_I \cdot I \qquad (0 \le I \le 2000) \tag{8}$$

$$\alpha_{co2} = \begin{cases} a_{co2} co2 + c_{co2} & (100 \le co2 < 500) \\ 1 & (co2 \ge 500) \end{cases} \tag{9}$$

where a_I, a_{co2}, and c_{co2} are coefficients at the time of assuming that α_I and α_{co2} can be expressed with a linear function here. Then the plant growth model of cultivation phase j of plant i under sequential cultivation, a procedure of cyclic cultivation-harvest which divides planting in a cultivation bed and shifts planting phases, can be expressed as;

$$dx_{ij} \big/ dt = \alpha_i x_i \left(1 - x_{ij} \big/ x_{mi}\right) \tag{10}$$

where, i represents the plant type and j expresses the cultivation stage of the plant. Accordingly, the plant growth model of the entire plant cultivation module is;

$$dx \big/ dt = \sum_{i=1}^{M} \sum_{j=1}^{N_i} dx_{ij} \big/ dt \tag{11}$$

where M expresses the maximal number of cultivated plants, and N_i the maximal number of cultivation stages of a specific plant.

HUMANS

The intensity of human activity is expressed by an activity index function [7] $z(t)$;

$$z(t) = \left(1 - A\cos(2\pi t / T)\right) \tag{12}$$

where A is the amplitude of an activity index ($0 < A < 1$), t the time (min), and T the period of an activity, usually a day in minutes.

Among a human's material I/O, O_2 and CO_2 are fluctuated by $z(t)$, while predetermined quantities of meal and discharge are carried out at a predetermined time.

O_2 SEPARATOR

An O_2 separator is equipment which separates O_2 from air. The separative capacity of the present equipment is assumed to always be constant. This equipment can determine on/off once an hour.

CO_2 SUPPLIER

A CO_2 supplier is equipment which supplies CO_2 to a plant cultivation space from a CO_2 tank by differential pressure. The present equipment can determine on/off once in 3 minutes.

O_2 SUPPLIER

An O_2 supplier is equipment which supplies O_2 to a human habitation space from an O_2 tank by differential pressure. The present equipment can determine on/off once in 3 minutes.

CO_2 SEPARATOR

A CO_2 separator is equipment which separates CO_2 from air. The present equipment can determine on/off once an hour. The separative capacity of this equipment v_{co2} is modeled as;

$$v_{co2} = \begin{cases} a_{co2} \cdot co2 & (0\,ppm \le co2 < 2000\,ppm) \\ c_{co2} & (co2 \ge 2000\,ppm) \end{cases} \tag{13}$$

where $co2$ is the carbon dioxide concentration, a_{co2} and c_{co2} are coefficients when v_{co2} is assumed to be expressed with a linear function saturating at 2000 ppm.

SOLID WASTE PROCESSOR

A solid waste processor is equipment that uses physicochemical processing to decompose organic waste into inorganic substances such as water, carbon dioxide, nitric acid, and ammonia. The present processor requires 8 hours for a processing cycle, and therefore can perform only three operations per day at the maximum. The operation of the solid waste processor is planned using fuzzy inference based on knowledge-based control.

RESULTS

SIMULATION CONDITION

This simulation included one human, and food was supplied by food production using only soybean plants. As the present simulation is aimed to propose a design method for the ALSS material circulation control system using an intelligent control, only soybean plants were used. The crop cultivation quantity was 735 g/day in dry mass, and the cultivation area was 120 m^2. The cultivation was divided into 16 stages, and sequential cultivation of a 12-hour dark term and a 12-hour light term was conducted. An extra 5 days of food is stored for emergency. The regular throughputs of the present O_2 separator, CO_2 supplier, O_2 supplier, CO_2 separator, and solid waste processor were 4.35 g/min, 4.86 g/min, 1.21 g/min, 3.38 g/min, and 1,012 g (dry mass)/8h. The capacities of O_2 and CO_2 tanks were 6,258 g and 6,998 g. As for the human habitation space, the capacity was 150 m^3, CO_2 concentration was set to 400 ppm, and O_2 concentration was set to 20.96%. For the plant cultivation space, they were 269 m^3, 700 ppm, and 20.93%.

This simulation judges the operation of the processors shown in Fig.8: the O_2 separator, CO_2 supplier, O_2 supplier, and CO_2 separator in the rule-based control level, and the solid waste processor of the plant cultivation module in the knowledge-based control level. The other processors, the O_2 recycler and the solid waste processor of the human habitation module, are operated according to a predetermined schedule. The application of intelligent control was inaugurated in the closed system mode after plant sequential cultivation was completed in 80 days, and continued for 120 days until day 200. The values of the parameters for the Reinforcement Learning of agents at this time are α= 0.1, γ= 0.99, and T= 0.1.

SIMULATION RESULTS

Here, we have a case treatable solely with by rule-based control and a case treatable by both rule-based control and knowledge-based control. The former presents a case when the potential of the CO_2 separator declines. Whether an agent is adapted for the new environment when the environment change is analyzed from the average of the on/off switching frequency and reward acquisition frequency by learning. The latter, when knowledge-based control needs to be used, shows a case when the crop cultivation schedule is altered. The solid waste processor without knowledge-based control is operated once per day according to the predetermined schedule. The shift of the crop cultivation stage by one full stage sways the balance of O_2, CO_2, and waste. Here analysis as to whether the implementation of knowledge-based control enables designing an operation schedule for the solid waste processor considers this.

When the capability of the CO_2 separator has declined

Table 3 shows the averages of the on/off switching frequency of the CO_2 separator and reward acquisition frequency before and after the capability deterioration when the capability of the CO_2 separator has declined 50% after the 141st day. The capability deterioration caused the average drop of switching frequency from 7.50 times / day to 2.87 times / day. This is because the switching frequency was reduced in order to compensate for capability deterioration, and ongoing operations were carried out. Next, when no capability deterioration took place, the reward acquisition frequency dropped from 0.40 times / day to 0.28 times / day, since learning had already progressed. However, when capability deteriorated, it increased from 0.42 times / day to 0.83 times / day, since learning was promoted in order to adjust to the new environment. The learning of an agent was appropriately carried out due to an environmental change.

Fig. 9 shows the fluctuations of the switching frequency of the CO_2 separator in the same case. Since the capability of the CO_2 separator had declined 50% after the 141st day, its switching frequency dropped suddenly. The on/off switching frequency was reduced due to shifting for ongoing operation as previously mentioned. This is a result where an agent adjusted itself to a new environment with learning within a day (24 steps).

When the crop cultivation schedule is altered

The change of biomass is shown in Fig.10, when no crops are being cultivated in cultivation stage 5 (day 101 - 180) but crops for two stages are cultivated simultaneously in cultivation stage 6 (day 106 - 185). A case with no alteration in the crop cultivation schedule is also shown for comparison. The alteration of the crop cultivation schedule caused a slight decrease in biomass from day 101 - 180. Then crops for two stages were harvested on day 185, which is because crops for cultivation stage 5 were cultivated with a delay of 5 days. This reduced O_2 production and CO_2 consumption by photosynthesis. Thus, as Fig. 11 demonstrates, the O_2 quantity fell below the lower limit of the tank in the case without knowledge-based control, while the O_2 quantity was maintained within the limits of the O_2 tank capacity with knowledge-based control. This is because the operation schedule of the solid waste processor was designed considering the long-term fluctuations of the O_2 quantity in the O_2 tank, CO_2 quantity in the CO_2 tank, and waste in the waste tank. CO_2 quantity was maintained within the limits of the CO_2 tank capacity irrespective of the existence of knowledge-based control, as shown in Fig. 12. The amplitude fluctuation of substances in the tank at this time is compared in Table 4. The use of intelligent control suppressed the amplitudes; from 5,439 g to 4,568 g in the case of the O_2 tank, and from 5,062 g to 4,565 g in the case of the CO_2 tank.

CONCLUSION

When the capability of the CO_2 separator declines 50%, the results suggest that rule-based control using Reinforcement Learning enables a new operation procedure when the environment changes. When the crop cultivation schedule is altered, the results suggest that the addition of knowledge-based control using fuzzy inference to rule-based control enable goal-driven designing of the operation schedule of the solid waste processor in unknown environment. The hierarchized combination of data-driven rule-based control and goal-driven knowledge-based control allow us to implement long-term strategy planning in unknown environment as well as short-term environmental change, and the simulation result was shown as an example. The authors would like to study the application of this procedure to water circulation systems and other cases in the future.

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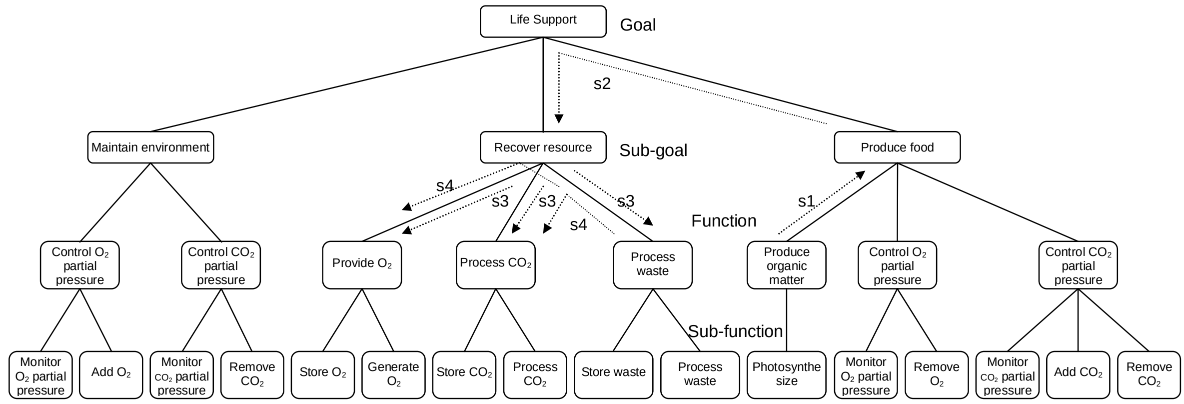
CONTACT

Hiroyuki Miyajima
Tokyo Jogakkan College
1105 Tsuruma, Machida-shi, Tokyo 194-0004 Japan
E-mail : miyajima@m.tjk.ac.jp
Telephone: +81-42-796-9464
Facsimile: +81-42-799-2652



Showing only functions related to the circulation of O_2 and CO_2.

Fig. 4 Functional structure of ALSS

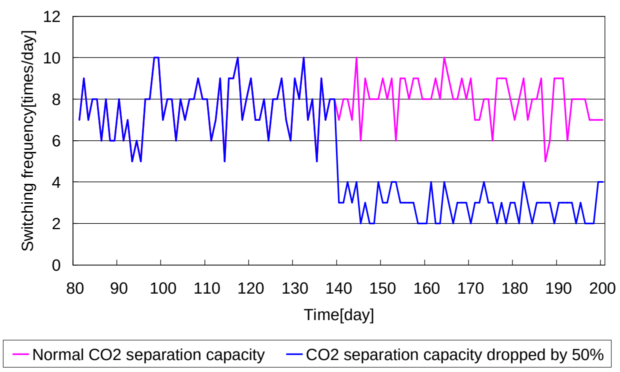


Fig. 9 Variation of switching frequency of CO_2 separator when CO_2 separation capability declined 50%

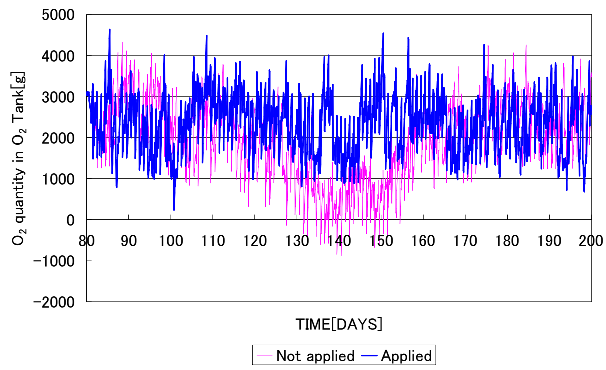


Fig. 11 Change of oxygen in O_2 tank

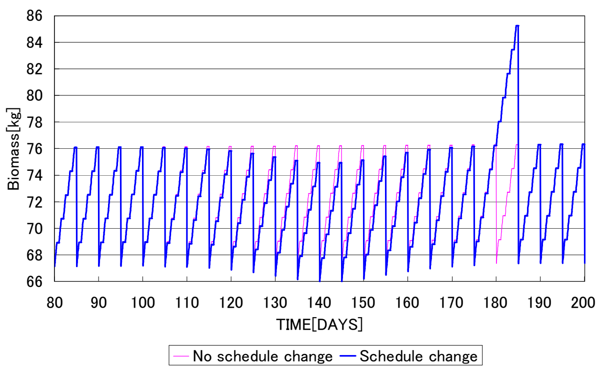


Fig. 10 Change of biomass in plant cultivation module

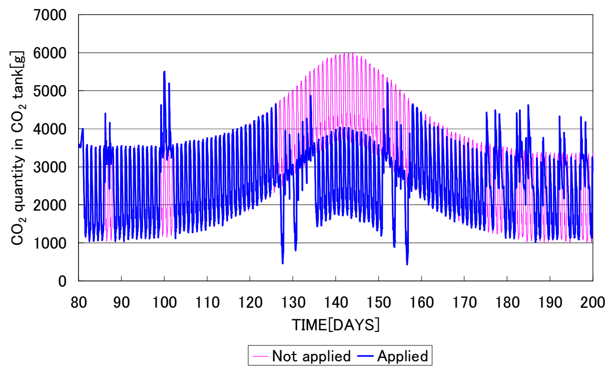


Fig. 12 Change of carbon dioxide in CO_2 tank

Table 1 Definition of risk levels

Substance quantity		Risk level
No less than	No more than	
Maximum limit		3
Allowable maximum	Maximum limit	2
(Set point + Allowable maximum) / 2	Allowable maximum	1
(Set point + Allowable minimum) / 2	(Set point + Allowable maximum) / 2	0
Allowable minimum	(Set point + Allowable minimum) / 2	-1
Minimum limit	Allowable minimum	-2
	Minimum limit	-3

Table 2 Fuzzy control rules

Fuzzy label of p		CO_2 Tank A_{i2}						
		NB(-3)	NM(-2)	NS(-1)	ZO(0)	PS(1)	PM(2)	PB(3)
O_2 Tank A_{i1}	NB(-3)							
	NM(-2)							
	NS(-1)							
	ZO(0)	PS	ZO					
	PS(1)	PM	PS	ZO				
	PM(2)	PB	PM	PS	ZO			
	PB(3)	PB	PB	PM	PS			

NB : Negative Big, NM : Negative Medium, NS : Negative Small,
ZO : Zero, PS : Positive Small, PM : Positive Medium, PB : Positive Big
The label of the fuzzy set corresponds to risk level in ().

Table 3 Average switch frequency and average reward acquisition frequency of CO_2 separator when CO_2 separation capability declined 50%

Term	Normal CO_2 separation capability		CO_2 separation capability declined 50%	
	Switching Frequency	Reward Acquisition Frequency	Switching Frequency	Reward Acquisition Frequency
[day]	[times/day]	[times/day]	[times/day]	[times/day]
81-140	7.57	0.40	7.50	0.42
141-200	8.02	0.28	2.87	0.83

Table 4 Comparison of amplitude fluctuation of substances in the tank

KNOWLEDGE-BASE CONTROL	O_2 Tank			CO_2 Tank		
	Maximum[g]	Minimum[g]	Amplitude[g]	Maximum[g]	Minimum[g]	Amplitude[g]
Nonuse	4557	-883	5439	6009	947	5062
Use	4641	73	4568	5510	945	4565