



A multi-agent based control scheme for accelerator pre-injector and transport line for enhancement of accelerator operations

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ABSTRACT

Reliable accelerator operation requires control system with higher level of automation, flexibility, robustness, and optimisation. In this paper a multi-agent system based control scheme is presented for optimal control of accelerator system that improves the plant performance in wide-range of operations. The multi-agent based control schemes for accelerators have been reported in literature. But the scheme proposed in this paper differs significantly from the existing schemes. In this work the agent architecture is formulated based on the control requirements of pre-injector accelerator subsystem (Microtron in particular) and transport line of synchrotron radiation sources. The scheme consists of two software agents at supervisory level that work in an autonomous manner for the optimized control of dynamic system. The Microtron agent architecture augments model assisted adaptive controller for realizing feedback control action at lower layer and goal based logic controller with pre-structure model identifier along with the pattern recognizer at supervisory layer. The TL-1 agent has a model-based, goal-based modular architecture and optimizes the TL-1 control using differential evolution based algorithm. The simulation results of applying this scheme to model of Microtron and Transport Line-1 of INDUS complex shows that this approach is very effective in optimizing the Microtron and TL-1 tuning.

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Introduction

Multi-agent based control schemes has been proposed by many researchers for exercising the robust control for large scale industrial system like power plants, power distribution systems, cement industry, ship board automation systems and accelerator control systems [1-5]. The existing multi-agent based control architectures for accelerator control [5- 12] could not be used directly for exercising the intelligent agent for controlling Microtron like accelerators, which exhibits dynamic nonlinear input-output behavior. Agent architecture for such systems requires augmenting functionality for adaptive feedback controller, dynamic and static model identifiers, and system state predictors based on historical data along with the supervisory level optimisation, communication, coordination and planning functionalities.

For controlling dynamic nonlinear systems using multi-agent based approach researchers have proposed different single agent architectures and organisation for multiple agents. J. D. Head et.al. [13] and S. Jin. et.al. [14] has proposed a three level based agent organisation with high level agents provide the man-machine-interface functionalities, at middle level the data base handling, task delegation and monitoring functionalities are handled, the lower most level implements the feedback and feedforward controllers with PI gain optimizer. The gain optimizer considers the current output of the plant and simulates the plant's response to feedback controllers using candidate gain values. Based on the response of the plant model, new candidate gain values are generated and tested. This process continues

until the current set of candidate gain values meet all criteria deemed necessary in order to be considered acceptable. Once a set of optimal gains has been found, they are sent to the Feedback agent for immediate implementation. For generating the model of subsystems neural network based off-line and on-line identifiers are proposed.

S. Kamalasan [15, 16] has shown that the multi-agent based approach can be effectively used for controlling the dynamic systems showing multiple modes and drastic parametric jumps. Single link flexible robotic manipulator was controlled using three agents. The first agent is a heuristic based multiple fuzzy reference model generator that moves the reference model, mapping the system auxiliary state when it shows multi modality. This agent generates suitable reference model structure at every time instant. The second agent is a radial basis function neural network based controller that is used to augment the traditional model reference adaptive control in the presence of system functional uncertainty. Main emphasis was given to the use of neural network to approximate inverse dynamics of the plant working in parallel with a linear adaptive control law. The third agent is the traditional model reference adaptive controller which adaptively controls the system, linearises the parameters over a specific domain and forces the output or other plant variables to a suitable reference model structure.

Ben Nasr et.al.[17] proposed a model predictive control of a non linear fast dynamic system based on the multi-agent concept. The global system was first decomposed into sub-systems

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independent of one another. For each sub-system a model predictive control unit was made constituting the agent controller. Based on the analytical solution corresponding to the solution of the local receding horizon sub-problems, a logic unit was designed which by switching tries to find the best sequence of actions sent to the nonlinear system that gives the desired trajectory. In this way the sequences of actions were identified that bring the global system in a desired trajectory avoid any violation constraints on actions. A fuzzy controller was also made with an objective to handle the results of the actions on the global system and monitor the closed-loop system.

Agent-based control offers the ability to learn the patterns in system dynamics and use this information in determining the optimal, or near optimal control schema. Further to this by propagating this information among different agents in a multi-agent environment the global goals and global constraints could be easily handled. Such learning capabilities have not been sufficiently addressed in the literature. The current approach limits the learning ability more or less to online and offline system model identification only. Further to this almost all of the strategies rely upon using the neural network based models for modeling the nonlinear system. This requires a large amount of data set to be generated for offline identification and validation there by increasing the offline identification time. This can degrade the system performance in case such identification is needed more often for example for dynamic systems where the system model is needed to predict the faraway operating points. A less data driven approach could be the use of predefined model structure in the static model identification block where the best suited predefined model structure can be found according to the problem domain separately.

This paper presents an agent-based methodology for controlling the pre-injector and transport line operations. The agents learn the patterns observed in the system dynamics for both short-term and long-term basis and optimize there individual operations as well as there joint goals based on the learned patterns. The Microtron agent architecture augments model assisted adaptive controller for realizing feedback control action at lower layer and goal based logic controller with pre-structure model identifier along with the pattern recognizer at supervisory layer. The TL-1 agent has a model-based, goal-based modular architecture and optimizes the TL-1 control using differential evolution based algorithm. The rest of the paper is organized as follows. Section 2 describes the accelerator system and its subsystem models used in this work, section 3 describes the proposed multi-agent based accelerator control scheme with individual agent architectures. Section 4 gives the simulation results followed by the conclusion.

The Accelerator System

The accelerator system comprises of three main parts; Microtron: it is a small accelerator which accelerates the electron beam upto 20MeV. It acts as pre-injector to synchrotron accelerator named Booster; Booster: it is another accelerator which accelerates the electron beam from 20MeV to 450MeV and 550MeV for injection to INDUS-1 and INDUS-2 respectively; TL-1: It is the transport line between Microtron and Booster accelerators which transfers the electron beam from one accelerator to other accelerator and serves the purpose of matching the parameters of beam available from Microtron to that of beam acceptance parameters at the Booster injection septum. The flow of beam between three parts is first beam is

produced by the Microtron accelerator it then enters to the TL-1 which transports it to the Booster injection point.

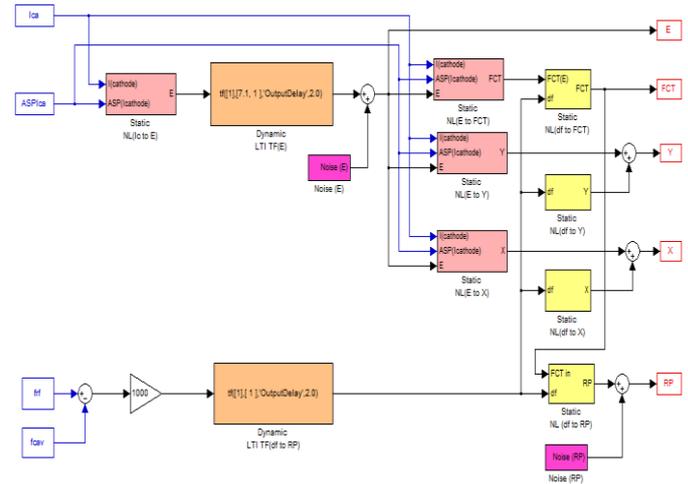


Figure 1. Simulink block diagram for Microtron model
The Microtron Model

The model of Microtron currently used in the development of the multi-agent system is based on the experimental identification of interdependence between different parameters. It is modeled as a four-input five-output nonlinear Simulink model shown in figure 1. The inputs into the system are Cathode current (I_{ca} in A) that controls the temperature of LaB₆ cathode inside Microtron RF cavity, RF frequency (f_{rf} in GHz) that provides the basic RF signal which is amplified by presiding amplifier stage and fed to the RF cavity for producing the required electric field in the cavity, acceleration start point in terms of I_{ca} ($ASPI_{ca}$ in A) which defines the system state and depends of various factors, Cavity resonant frequency (f_{cav} in GHz) it is the resonant frequency of the cavity at the particular time and depends primarily of the cavity temperature and electron emission level in cavity. The outputs of the model are Emission (E in V) which gives the measure of electrons emitted from cathode, Fast current transformer signal (FCT in V) which gives the measure of electrons actually accelerated to 20MeV level, beam position (X and Y in mm) at the extraction point, reflected power signal (RP in V) that gives the measure of power reflected by the cavity. The Eq. 1 to 9 gives the interdependence between different parameters used for Microtron modeling.

$$E = \begin{cases} 4.35I_{ca} - 126.6 & \text{for } I_{ca} \leq ASPI_{ca} \\ 1.324I_{ca} - 35.11 & \text{for } I_{ca} > ASPI_{ca} \end{cases} \quad (1)$$

$$FCT_E = \begin{cases} 0.2 & \text{for } I_{ca} \leq ASPI_{ca} \\ -0.1318E^2 + 1.389E - 3.036 & \text{for } I_{ca} > ASPI_{ca} \\ 0 & \text{for } E < 3.1 \\ 0.1 & \text{for } E > 7.4 \end{cases} \quad (2)$$

$$FCT = \begin{cases} 0.01 & \text{for } \delta f < -0.6 \text{ or } \delta f > 0.6 \\ -5.007\delta f^5 - 2.889\delta f^4 + 0.03362\delta f^3 - 0.3748\delta f^2 \\ \quad + 0.3415\delta f + FCT_E & \text{for } -0.6 < \delta f < 0.6 \\ 0 & \text{for } FCT < 0 \end{cases} \quad (3)$$

$$X_E = \begin{cases} 0.08935E & \text{for } I_{ca} \leq ASPI_{ca} \\ 0.2935E & \text{for } I_{ca} > ASPI_{ca} \end{cases} \quad (4)$$

$$Y_E = \begin{cases} 1.391E & \text{for } I_{ca} \leq ASPI_{ca} \\ 4.571E & \text{for } I_{ca} > ASPI_{ca} \end{cases} \quad (5)$$

$$X_{\delta f} = 0.9196 \left(1 - e^{-\frac{(\delta f)^2}{0.2507}} \right) \quad (6)$$

$$Y_{\delta f} = 1300 \left(1 - e^{-\frac{(\delta f)^2}{60.16}} \right) \quad (7)$$

$$RP = 0.115 \left(1 - e^{-\frac{(\delta f)^2}{0.5758}} \right) + C_0 \text{ Where } C_0 = 0.0672 \frac{(FCT_{max} - FCT)}{FCT_{max}} \quad (8)$$

where $\delta f = (f_{rf} - f_{cav})$ is the deviation of RF generator frequency from the cavity resonant frequency expressed in MHz, and the beam position X and Y using Eq. 4 to 7 are calculated as below.

$$\text{Beam Position } (X, Y) = \begin{cases} X = X_E + X_{\delta f} - 1.6 \\ Y = Y_E + Y_{\delta f} - 24.8 \end{cases} \quad (9)$$

Noise at emission signal $Noise(E)$ and noise at the reflected power signal $Noise(RP)$ are modeled by autoregressive model given by Eq. 10 and 11.

$$Noise(E) = \frac{e(t)}{1 - 0.9982q^{-1} - 0.0007436q^{-2}} \quad (10)$$

Where $e(t)$ = white noise

$$Noise(RP) = \frac{e(t)}{1 - 0.9983q^{-1} - 0.000969q^{-2}} \quad (11)$$

Where $e(t)$ = white noise

And the dynamic response transfer function (TF) for emission signal (E) and reflected power (RP) are modeled as given by Eq. 12 and 13.

$$TF(E) = \frac{e^{-2.0s}}{7.0s + 1} \quad (12)$$

$$TF(RP) = e^{-2.0s} \quad (13)$$

For calculating the different settings the Microtron agent uses the static model thus bypassing the dynamic TF for E and RP.

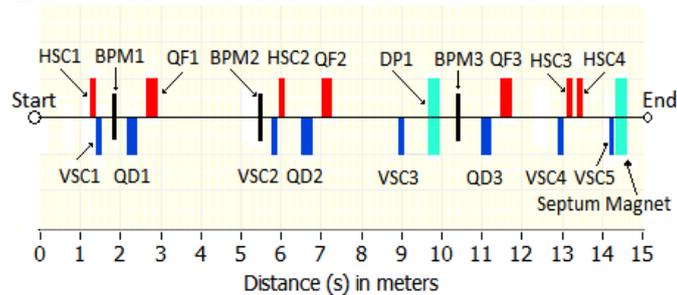


Figure 2. Layout of TL-1

The TL-1 Model

The layout of TL-1 is shown in Figure 2 using which the model of TL-1 is constructed by multiplying the transfer matrixes of individual elements. This model accepts the macro particle beam with attributes (x, y, x', y') and magnet settings $S = [I_1, I_2, \dots, I_n]$ to produces the attributes (x, y, x', y') for macro particles at BPM1, BPM2, BPM3 locations and at the end of TL-1. The particle at the start of TL-1 with $X = [x_0, x_0']$ and $Y = [y_0, y_0']$ are transferred to the end of TL-1 using Eq. 14

and 15. Similarly the transformations from TL-1 start to the respective BPM are given by Eq. 16 to 21

$$X_{End}^T = M_3^x C_2^x M_2^x C_1^x M_1^x X_0^T \quad (14)$$

$$Y_{End}^T = M_3^y C_2^y M_2^y C_1^y M_1^y Y_0^T \quad (15)$$

$$X_{BPM1}^T = M_{BP1}^x C_1^x M_1^x X_0^T \quad (16)$$

$$Y_{BPM1}^T = M_{BP1}^y C_1^y M_1^y Y_0^T \quad (17)$$

$$X_{BPM2}^T = M_{BP2}^x C_1^x M_1^x X_0^T \quad (18)$$

$$Y_{BPM2}^T = M_{BP2}^y C_1^y M_1^y Y_0^T \quad (19)$$

$$X_{BPM3}^T = M_{BP3}^x C_2^x M_2^x C_1^x M_1^x X_0^T \quad (20)$$

$$Y_{BPM3}^T = M_{BP3}^y C_2^y M_2^y C_1^y M_1^y Y_0^T \quad (21)$$

Where the Matrix

$$M_1^x, M_2^x, M_3^x, M_1^y, M_2^y, M_3^y, M_{BPM1}^x, M_{BPM1}^y, M_{BPM2}^x, M_{BPM2}^y, M_{BPM3}^x,$$

M_{BPM3}^y are calculated for the typical values of magnet settings at which the TL-1 is normally operated is given as below

$$M_1^x = \begin{bmatrix} 1 & 1.3280 \\ 0 & 1 \end{bmatrix} \quad M_2^x = \begin{bmatrix} -0.9556 & -0.5919 \\ 0.8418 & -0.5250 \end{bmatrix}$$

$$M_3^x = \begin{bmatrix} -0.7580 & -0.9286 \\ 0.6410 & -0.5340 \end{bmatrix}$$

$$M_1^y = \begin{bmatrix} 1 & 1.4680 \\ 0 & 1 \end{bmatrix} \quad M_2^y = \begin{bmatrix} -2.1105 & 3.8592 \\ -0.8149 & 1.0163 \end{bmatrix}$$

$$M_3^y = \begin{bmatrix} -0.8901 & 0.3016 \\ -0.0284 & -1.1138 \end{bmatrix}$$

$$M_{BP1}^x = \begin{bmatrix} 1 & 0.6840 \\ 0 & 1 \end{bmatrix} \quad M_{BP2}^x = \begin{bmatrix} -0.30238 & 0.99932 \\ -0.84182 & -0.52496 \end{bmatrix}$$

$$M_{BP3}^x = \begin{bmatrix} -0.87364 & 0.8775 \\ -0.6402 & -0.50159 \end{bmatrix}$$

$$M_{BP1}^y = \begin{bmatrix} 1 & 0.5440 \\ 0 & 1 \end{bmatrix} \quad M_{BP2}^y = \begin{bmatrix} -1.62313 & 3.25144 \\ -0.81491 & 1.01634 \end{bmatrix}$$

$$M_{BP3}^y = \begin{bmatrix} -0.97504 & 5.0733 \\ -0.44863 & 1.30872 \end{bmatrix}$$

And the operations $C_1^x, C_2^x, C_1^y, C_2^y$ are given as below

$$C_1^x = \begin{cases} x_1 = x_0 \\ x_1' = x_0' + (I_{HSC1} / 13.0) \end{cases}$$

$$C_2^x = \begin{cases} x_1 = x_0 \\ x_1' = x_0' + (I_{HSC2} / 13.0) \end{cases}$$

$$C_1^y = \begin{cases} y_1 = y_0 \\ y_1' = y_0' + (I_{VSC1} / 13.0) \end{cases}$$

$$C_2^y = \begin{cases} y_1 = y_0 \\ y_1' = y_0' + (I_{VSC2} / 14.0) \end{cases}$$

The Booster Model

The booster model accepts the beam composed of n number of macro particle and calculates the normalized booster current

successfully injected into the booster using Eq. 22 by evaluating the pass/lost condition for each macro particle. The pass/lost condition for each particle is evaluated using Eq. 23 and 24. These equations are calculated by obtaining the acceptance in phase space for Booster using the MAD [18] based Booster model for the typical magnet settings at which Booster is normally operated.

$$I_{BR} = \frac{1}{n} \sum_{i=1}^n f_B^x(i) \times f_B^y(i) \quad (22)$$

$$f_B^x(i) = \begin{cases} 1 & \text{for } 0.363x_i^2 - 0.663x_i x_i' + 3.328x_i'^2 \leq 33.765 \\ 0 & \text{for } 0.363x_i^2 - 0.663x_i x_i' + 3.328x_i'^2 > 33.765 \end{cases} \quad (23)$$

$$f_B^y(i) = \begin{cases} 1 & \text{for } 1.83y_i^2 + 0.364y_i y_i' + 0.568y_i'^2 \leq 51.359 \\ 0 & \text{for } 1.83y_i^2 + 0.364y_i y_i' + 0.568y_i'^2 > 51.359 \end{cases} \quad (24)$$

Where x and y are in millimeter and x' and y' are in millirad the TL-1 agent uses this model for predicting the current injected into the booster under different operating conditions.

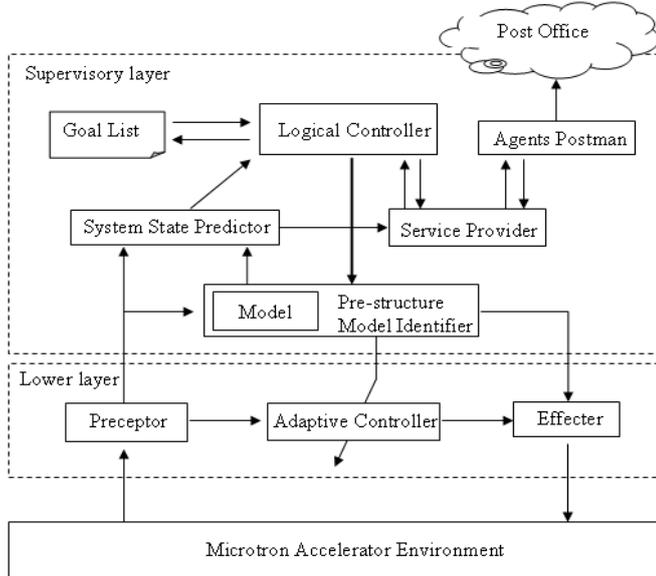


Figure 3. Microtron Agent architecture

Multi-agent based accelerator control

Microtron Agent:

The Microtron agent is made with the architecture shown in figure 3. The agent architecture comprises of two loops, the first loop: comprised of “preceptor”, “adaptive controller” and “effector” blocks. This loop is responsible for continuously maintaining the machine operating point under dynamic conditions. The loop works on the principle of sense-think-control cycle where the accelerator environment is continuously sensed and if some drift in the operating point is observed the corresponding corrective action is calculated by the adaptive controller and applied to the accelerator environment through effector.

The second loop is the supervisory loop responsible for autonomously controlling the agent actions and the interaction with other agents. The “pre-structure model identifier” block when required /asked by the “logical controller” identifies the plant model in the pre-structured model form by directly taking the control of “effector” and “preceptors” and using the predefined action recipe. This block also provided this identified model to other blocks like “system state predictor”

block, “adaptive controller” block and “logical controller” block for their functions.

The “system state predictor” block continuously tries to learn the system dynamics and predicts the system dynamics for future n steps using the auto-regressive moving average with exogenous (ARMAX) algorithm.

This block also provides the functionalities of predicting the future machine states/parameters under the influence of dynamics using the currently identified Microtron model. “Service provider” block is the communication interface of the agent with the other agents. This block is responsible for serving the requests obtained from different agents and from “logic controller” which requires some data from other agents. The “postman” is the communication medium between the agent and the post office for exchange of messages between different agents. The “logic controller” is the brain of the agent and is responsible for managing and synchronizing all the activities of the agents towards the achievement of goals.

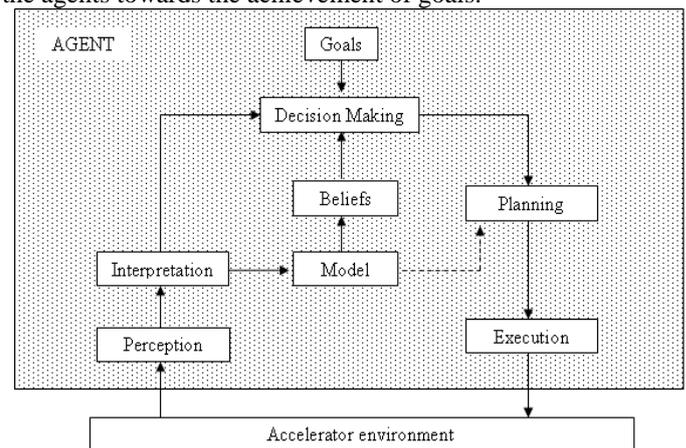


Figure 4: TL-1 agent architecture

TL-1 Agent:

The TL-1 agent is developed with a model-based, goal-based modular architecture shown in figure 3. [19] and optimizes the TL-1 control using differential evolution based algorithms. The “Perception” and “Execution” blocks directly interact with the accelerator environment. In TL-1 case it will interact with the TL-1 power supplies and beam diagnostic devices (Fast Current Transformer (FCT) through Oscilloscope, Fluorescent Beam Position Monitor (BPM) screens). Function of the “Perception” block is to read different P/S settings and read-back values, FCT & Oscilloscope traces and BPM images. Depending upon the read data it then generates the appropriate event. Events are passed directly to the respective blocks in the form of messages along with the required data. The “Interpretation” block serves the purpose of processing the raw data acquired by the “perception” block to convert it to the required form in TL-1 this block extracts the beam position (x , y) and beam sizes (σ_x , σ_y) from the BPM images and the injection current value from FCT and CRO traces. “Beliefs” block is the agent’s data storage. This stores the system state and other meta data required in the processing / decision making steps. “Goal” block contains the definition for all the goals and provision for enabling / disabling of goals. Definition of goal comprises of plan list. Plans in the list are the alternate plans by which the goal could be achieved in different system conditions. The position of the plan in the plan list decides its priority. The plan at higher level in the list has higher priority. The “Decision Making” block depending upon the current events and the agent beliefs decide the plans to be executed to achieve all the active

goals. It does this by evaluating the plan applicability function and selecting the highest priority applicable plan from the list for each active goal. The “Planning” block serves the purpose of executing the selected plan in synchronised/coordinated way and updating the active goal list. Each plan body comprises of sequence of actions i.e. steps to be followed to attain the desired goal. The “Execution” block sends the commands obtained from different blocks in the form of messages to machine components after checking them for the validity. The “Model” block in itself is an agent comprising of the TL-1 model and serves the purpose of providing the information about the probable outcome of the stated actions on the machine.

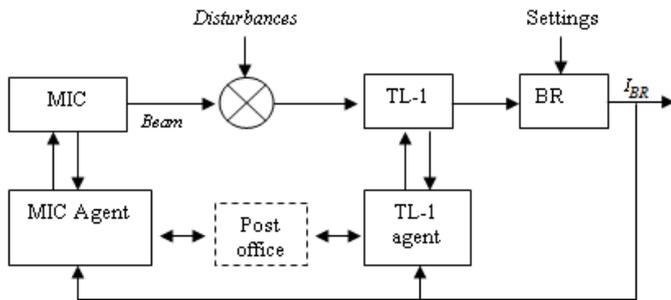


Figure 5: Block diagram of multi-agent based control of Microtron and TL-1

Multi-agent based control:

Figure 4 shows the multi-agent based control system block diagram for controlling Microtron and TL-1. The multi-agent based control of Microtron and TL-1 towards the cooperative tuning requires that both of the agents should try to maintain their individual operation to the optimum according to their local priorities on one hand and cooperatively decide their operating points such that their joint goal of increasing the overall injection current in the booster is achieved. This is achieved by jointly identifying the operating points which maximises the cost function J_1 given by Eq. 25. Subject to the conditions that the demand of change in the TL-1 magnet settings is to be reduced while always maintaining the required level of injection current in booster.

$$\max J_1 = I_{MIC}(x_t, x'_t, y_t, y'_t, OP_{MIC}) \times I_{TL1}(x_t, x'_t, y_t, y'_t, OP_{TL1}) \quad (25)$$

For the case of cooperative optimisation based on the dynamics learning the Microtron agent at the time of deciding the new operating point for optimisation cooperatively maximises the cost function J_2 given by Eq. 26 considering the n steps ahead future disturbances based on the past movement history provided by the “system state predictor” block.

$$\max J_2 = \sum_{i=1}^n I_{MIC}(x_i, x'_i, y_i, y'_i, OP_{MIC}) \times I_{TL1}(x_i, x'_i, y_i, y'_i, OP_{TL1}) \quad (26)$$

Simulation results

For checking the effectiveness of this scheme the system comprised of accelerator model, Microtron agent and TL-1 agent as shown in figure 5 is simulated. The results of the agent based control when beam coming out of Microtron is subjected to the disturbance shown in figure 6 for three different scenarios, scenario1: when both the TL-1 and Microtron agent works independently to achieve their individual goal, scenario 2: when both of the agents work cooperatively to maximize the booster injection current, and scenario 3: when both of the agents cooperatively with dynamics learning capability works to maximize the booster injection current with 20 steps ahead

predicted beam dynamic behavior were calculated for the beam disturbance shown in figure 6 . Figure 7 shows the injection current in booster for the three scenarios. Figure 8 shows the different operating points for which the TL-1 was adjusted by the TL-1 agent for the three scenarios. Figure 9 shows the beam current provided by the Microtron for the three different scenarios.

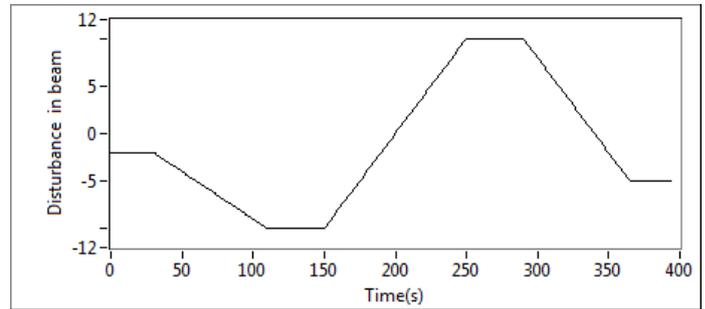


Figure 6 Disturbance in beam added at Microtron output

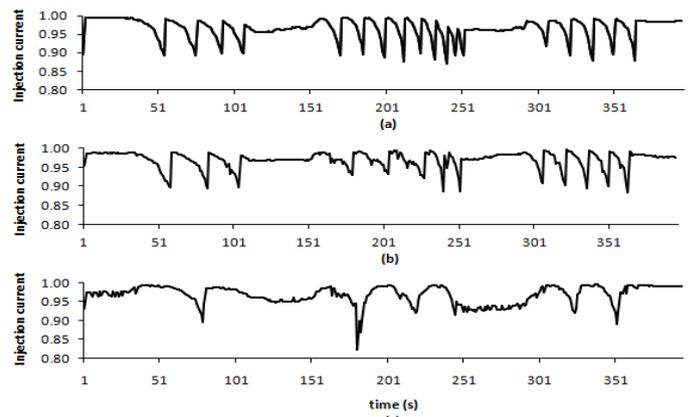


Figure 7: Normalized injection current in booster for (a) when Microtron and TL-1 agents optimize their operations individually (b) when both of the agents work cooperatively for optimizing the injection current as well as reducing the no of changes in TL-1 settings (c) When both of the agents work cooperatively with dynamics learning case.

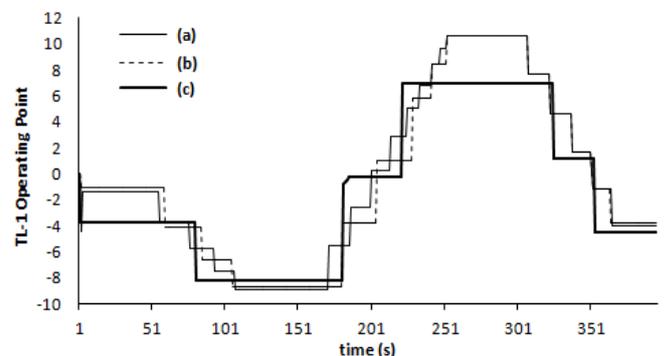


Figure 8 TL-1 operating points for which TL-1 was adjusted by TL-1 agent for (a) scenario 1 (b) scenario 2 (c) scenario 3. From Figure 7 (b) it can be seen that the booster current in case of cooperative optimization is showing lesser number of variation in Booster current with respect to the case when agents work individual (figure 7(a)). This variation further reduces with the application of the dynamics based learning algorithm (figure 7(c)). From figure 8 it can be seen that for the case of dynamics based learning the changes in operating point of TL-1 is minimum as compared to other two cases. From Figure 9 the effect of cooperative optimization in choosing the operating

points by Microtron agent can be seen clearly. Where for the scenario 1 the Microtron current remains always at its best operating value but for the other two scenarios the agent gives priority to the common goals and thus opted for slightly sub optimal operating points.

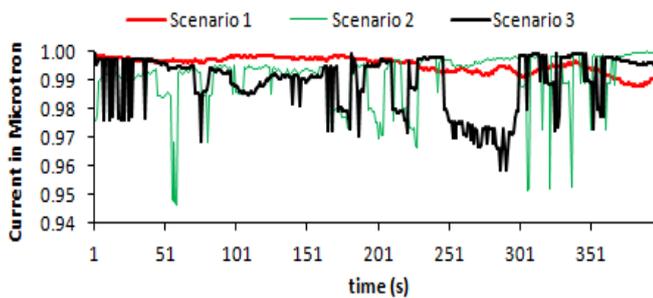


Figure 9 Beam current at Microtron output when Microtron is operated at different operating points by Microtron agent under different scenarios.

Conclusion

In this paper the application of a multi-agent based approach in control of pre-injector and transport line at synchrotron accelerator facilities was discussed. The novel concept of cooperative optimization with system dynamics learning capability for multi-agent based control approach was presented. The individual agent architecture for controlling Microtron and Transport line and their organization as multi-agent for cooperative control was designed. The simulation results of the presented concept for controlling the pre-injector accelerator Microtron and Transport line under the influence of disturbance on beam shows that this scheme can be used successfully for their optimal control without operator interventions.

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