parental function to 65% and a simultaneous step unmeasured disturbance $D(k) = 4$. In both the cases, the MPC tuning parameters $Q_y = 1,\ Q_{\Delta u} = 0.1,\ Q_u = Q_d = Q_z = 0$, $(\alpha_r,\ f_a) = (0,\ 0.3)$, the prediction horizon $p = 40$ and control horizon $m = 10$ are used. The *Tomlab-CPLEX* solver is used to solve resulting *miqp* optimization problems. From the figure it can be seen that the controller designed using the MoD approach is able to quickly achieve the desired setpoint, and stabilizes the system at the setpoint. In contrast, the controller relying on the linear ARX model oscillates around setpoint. In addition, the proposed algorithm produces less variation in the manipulated variable and provides uniform performance. This fact is also confirmed by the performance matrices J_e and $J_{\Delta I}$ given below:

$$J_e = \sum_{k=1}^{t/T_s} (PF(k) - PF^{goal})^T (PF(k) - PF^{goal}) \quad (34)$$

$$J_{\Delta I} = \sum_{k=1}^{t/T_s} (I(k) - I(k-1))^T (I(k) - I(k-1)) \quad (35)$$

where t represents total simulation time and T_s is a sampling time. The performance matrices J_e and $J_{\Delta I}$ represent measure of cumulative deviation of parental function from the goal and measure of cumulative variation in the intervention dosages, respectively. For the MoD approach, values of J_e and $J_{\Delta I}$ are 7.84×10^3 and 1.11×10^4, respectively, while using the linear ARX model based MPC, these values are 9.05×10^3 and 1.55×10^4, respectively. Thus, it can be concluded that the proposed algorithm yields superior performance and is suitable for the control of nonlinear hybrid systems.

V. SUMMARY

Applications of hybrid systems are becoming increasingly common in many fields. Recently, control engineering principles have been proposed for adaptive behavioral interventions [21]; these systems are naturally hybrid in nature. In this work, a Model-on-Demand Predictive Control (MoDPC) approach for control of nonlinear hybrid systems and its application to a simulated adaptive behavioral intervention are presented. The formulation uses a Model-on-Demand approach to obtain a local MLD model for the nonlinear hybrid system at each time step. MoD is a data-centric approach that uses a small neighborhood data around current operating point characterized by the regressor vector. The local MLD model generated by MoD estimator is then used to specify a model predictive control law that relies on multiple-degree-of-freedom tuning parameters [4]. Multiple-degree-of freedom tuning enables the speed of disturbance rejection and setpoint tracking affecting each output to be adjusted individually; this has intuitive appeal. The applicability and efficiency of proposed formulation is demonstrated on a hypothetical intervention problem intended for improving parental function in at-risk children. This problem exhibits nonlinear dynamics with inherent discrete events. From the simulation results, it can be concluded that the proposed MoDPC is useful for the control of nonlinear hybrid systems, displaying acceptable performance levels while simplifying the task of modeling.

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